Optimising Energy Performance of buildings through Digital Twins and Machine Learning: Lessons learnt and future directions

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Abstract—In recent years, the energy efficiency of buildings has received increasing attention due to climate change mitigation goals, and higher energy costs. This paper explores the integration of 3D models, IoT sensors, Digital Twins (DT), data-driven modeling, and Artificial Intelligence (AI), particularly Machine Learning (ML) algorithms, to enhance energy performance prediction and optimisation in existing buildings. By leveraging real-time data from IoT sensors, DTs provide a comprehensive digital representation of buildings, facilitating intelligent monitoring and control for enhanced energy efficiency and occupant comfort. This paper presents the development and application of a data-driven DT for an office building in Norway, focusing on energy performance prediction. Through a case study, specific outcomes and insights are gathered regarding the feasibility and benefits of this approach, together with its inherent limitations. The results highlight that significant advancements in energy efficiency could be achieved through predictive modeling and intelligent control strategies. In future, adaptation of these technologies requires addressing key challenges and advancing methodologies for broader implementation. By identifying and addressing these challenges, the integration of IoT sensors, DTs, and AI holds considerable scope for optimising building energy performance and advancing sustainability objectives.

Keywords—AI, Artificial Neural Network, energy efficiency, case study

I. INTRODUCTION

The building sector consumes more than one-third of the total electricity produced globally[1] and contributes substantially to Greenhouse Gas (GHG) emissions, making them pivotal for advancing environmental sustainability. Consequently, sustainable buildings play an important role in achieving the 2030 UN sustainable development goals[2]. As a result, governments worldwide are increasingly prioritizing initiatives and policies aimed at enhancing building energy efficiencies and promoting energy savings. In this respect, advancements in the building intelligence presents a significant opportunity for improving the energy efficiency of buildings. The revised Energy Performance of Building Directive (EPBD)[3] is the main legislative instrument defining requirements for energy efficiency in buildings across Europe. By 2050, the EPBD aims to achieve a highly energy-efficient and decarbonised building stock by transforming it into nearly zero-energy buildings (nZEB)[4].

It specifically focuses on the worst-performing buildings, and digital technologies can support both efficient building operation and renovation planning by collecting data from various sources for simulations, automation, and decision support. This reinforces the prospects for advancing digital twin-based optimisation of building energy efficiency in the future.

Digital Twins (DT) are virtual representations of physical objects or systems updated from real-time data, and use simulation, machine learning (ML), and reasoning to aid decision making [5]. The Digital Twin consortium defines DTs as "*a virtual representation of real-world entities and processes, synchronized at a specified frequency and fidelity. DTs use real-time and historical data to represent the past and present and simulate predicted futures. DTs are motivated by outcomes, tailored to use cases, powered by integration, built on data, guided by domain knowledge, and implemented in IT/OT systems*" [6] . In the context of buildings, DTs with the integration of IoT sensors offer several applications and advantages, particularly help facility managers to gain new operational insights such as real-time visibility into building energy consumption, demand, and energy usage patterns, as well as assist in monitoring energy performance of the building, optimising energy use and overall efficiency of the building. Being a virtual replica of the physical asset, DTs also offer the capability to model future behaviour of a building and anticipate how it will react to changes with predictions based on the present and historical data [7].

The recent, massive developments around DTs, IoT and connected sensor applications generate an increasing amount of data. To maximise the benefits offered by these digital solutions, the data should be leveraged to generate new knowledge such as visualisations of trends, anomalies, etc. AI plays a crucial role in processing the vast amount of data from the DTs by offering advanced algorithms and techniques for analyzing, interpreting, and extracting valuable insights from the large and complex datasets. By using AI as one of the building blocks when designing and building a DT, we can utilize the powerful capabilities within AI techniques to create a simulation and prediction of the energy consumption of the building. AI has the ability and power to interpret the complex correlations between the different sensors and metering

devices to predict the behaviour of the building when altering its energy usage. This predictive capability could empower facility managers to make informed decisions about energy optimisation strategies, thereby enhancing overall efficiency and sustainability in building operations.

Another key constituent of a building energy DT is how the information is visualised. Visualisation enhances the utility and effectiveness of DTs by transforming raw data into actionable insights facilitating informed decision-making, communication, and collaboration. There are numerous ways to visualise building DTs, their energy parameters, simulations, and predictions. Nevertheless, visualising it in 3D provide end-users with a more intuitive, immersive, and engaging experience that enhances their understanding and interpretation of complex datasets. By leveraging the spatial dimension to represent data in a more realistic and interactive manner, 3D visualisations enable users to explore, analyse, and communicate insights in ways that are not possible with traditional 2D visualisations.

The combination of above pioneering digital solutions, analytical methods and visualisation tools can play a crucial role in energy management and promoting the energy efficiency in the buildings. Thus, in this paper we aim to address the research gap in optimising the energy performance in existing buildings by introducing and investigating the potential of DT and AI technologies. In addition, we propose a standardized and interoperable data architecture for wider adaptation of these technologies for building energy management. The rest of the paper is structured as follows: The "Methodology" section presents our DT Framework and discusses its constituent parts. The "Case study and findings" section explains how our DT concept has been applied to one of the office buildings in Halden, Norway. The "Discussion" section exchanges our views about the findings and what we need to achieve a scalable DT platform for building energy optimisation followed by the "Conclusion" section concluding on the findings of the paper and future directions for the research in this area.

representation of the building, both static information such as digital building information in the form of 3D models, blueprints and dynamic information such as the building's energy performance parameters through the sensors are required. Following the acquisition of these data components, mathematical models and algorithms are required to effectively model, simulate, and predict the energy performance of a building for optimisation. Subsequently, after the data integration and analysis, dashboards and visualisation tools should be implemented in a DT platform to display real-time data streams, performance metrics, and key performance indicators (KPIs) associated with energy usage and efficiency. At this stage, a DT of a building could serve as a powerful tool for optimizing energy usage, improving operational efficiency, and enhancing overall sustainability performance. By providing real-time insights, predictive analytics, and advanced control capabilities, DTs empower users to make informed, data-driven decisions.

B. 3D model of the building

To establish a building DT in 3D, the first step is to obtain the precise geometry of the building. Typically, this information is sourced from the Building Information Modeling (BIM) files associated with the building. BIM models serve as digital representations of physical and functional characteristics of buildings and infrastructure. These models are three-dimensional (3D) and contain detailed information about various components of a building, including geometry, materials, spatial relationships, and building systems [8]. Originally conceived as a control tool for the project implementation and management process, BIM has huge potential for advancing building intelligence. However, its utilization is hindered by a substantial "interactivity" gap in accessing data [9]. Moreover, another key barrier for leveraging BIM for DTs is the unavailability of BIM models for the majority of existing buildings. In the absence of BIM models, one solution is to create the 3D model of the building using 3D modelling tools. However, this is often a resource-intensive and time-consuming process especially for larger buildings with complex geometries. For this reason, 3D scanning has been utilised for creating the 3D replica of the building for this study.
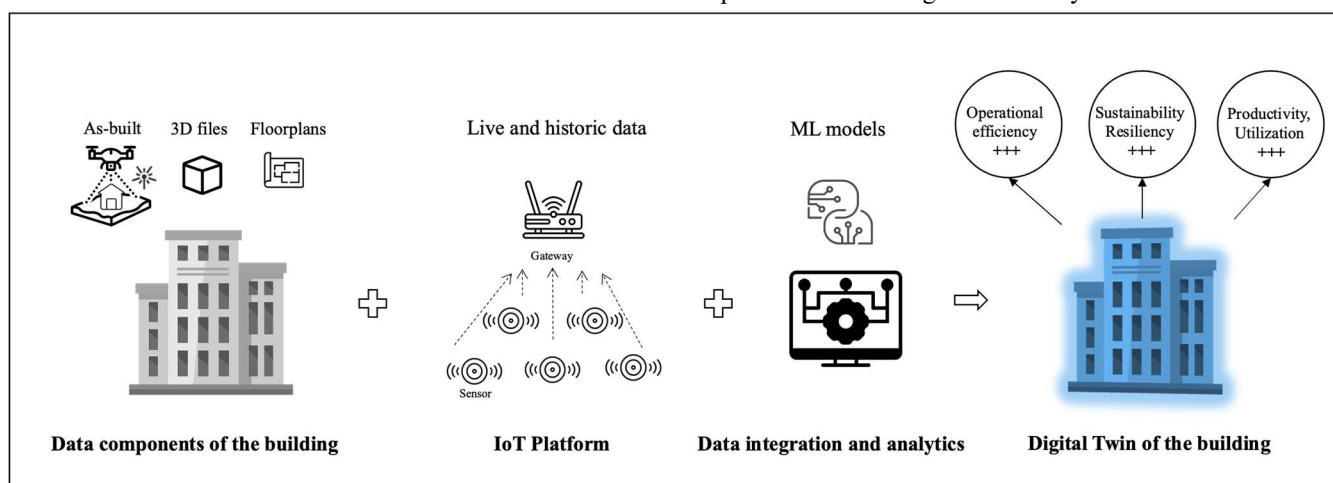

Fig. 1. Components of a building energy Digital Twin

II. METHODOLOGY

A. Digital twin framework design

Fig. 1 illustrates an overview of the components of an energy DT in 3D for a building. To construct a digital

3D scanning emerges as an efficient method for capturing as-built models of the buildings, offering accurate geometries and realistic visualisation when 3D models are not available. For this case study, various 3D scanning approaches have been devised for capturing and modelling both the exterior

and interior of the building. The outside of the building has been modeled using photogrammetry (Fig. 2), utilizing images captured by a drone. In total, 228 pictures were captured using DJI mini 2 drone from various angles and distances covering the whole outside area of the building. These images were then processed using the photogrammetry software tool 3DF Zephyr[10] for feature extraction, triangulation, point cloud generation, surface reconstruction and texture mapping. Meanwhile, laser scanning has been employed for capturing the interior of the building. Leica BLK360 precision imaging laser scanner and Leica cyclone FIELD 360 mobile application[11] were used for capturing and generating the 3D point cloud data of the building interior (Fig.4). The decision to leverage these technologies were made based on the assessment of required level of detail, limitations of the technologies and available resources.

Fig. 2. 3D model of the building generated using photogrammetry

C. Live measurements of the energy parameters of the building

Another crucial component of the energy DT involves acquiring live data from the building. Several IoT sensors were installed at various locations of the building for monitoring the Indoor Environment Quality properties such as temperature, humidity, CO_2 and for counting the occupants. These sensor measurements can be retrieved in real-time through APIs. In addition, energy related measurements from smart meters, external weather conditions are also retrieved through dedicated APIs to measure the overall electricity consumption of the building in real time. To be able to collect data from various sensors, ranging from old legacy sensors to modern sensors/IoT devices, there is a need to standardise and harmonise data according to a common data model and API. Two examples of the EU prioritizing standards are the Interoperable Europe Act[12] which aims to strengthen digital service infrastructures in the public sector across the EU, and the collection of standards in the Blueprint 1.0 [13] which supports the deployment of the European Data Spaces published by the Data Spaces Support Centre. The NGSI-LD standard[14] and the related technology stack from FIWARE [15] have been selected to achieve interoperability and comply with the Blueprint 1.0. At the core of the FIWARE technology stack, the context broker is the engine that receives standard API calls from a DT ecosystem and provides context information about building entities like hallways, meeting rooms, HVAC systems or the external environment. The context broker supports both queries and subscription to the context information. Based on these considerations, FIWARE compliant YGGIO Data infrastructure Management System (DiMS) middleware from Sensative[16] has been used for handling the data from the IoT devices.

D. Data-driven models for simulation and prediction of energy consumption

Based on the available sensor measurements described in the previous section and the data obtained from energimeter.no, which provides details on all the energy consumed by the building along with outdoor temperature data, our model focuses on estimating the energy required to maintain a comfortable temperature inside the building. Another aim of the model is to predict potential energy savings achieved by reducing the building's energy consumption. Given the number of temperature sensors across various floors and rooms, our aim was to devise a model capable of estimating the temperature at each sensor point. To achieve this, a model that predicts temperature increments based on energy consumption was developed. Consequently, the temperature difference between indoor and outdoor temperatures was chosen as the output of the network. The energy consumption, outdoor temperature, temperature of the air entering the ventilation system and the frequency of the ventilation fan were selected as inputs for the model. The reason for also selecting the frequency of the ventilation fan is because it is typically shutdown during the night, which could impact room temperatures. While radiators installed in every room serve as the primary source of heat in the building, the temperature within the ventilation system also influences room temperatures.

The model was constructed as a fully connected neural network model (dense neural network). In the input layer, 4 nodes were incorporated to represent energy consumption, outside temperature, ventilation fan frequency, and ventilation system temperature. The model featured 3 hidden layers of the Dense type using the RELU activation function, comprising 20,10 and 20 nodes and the output of the model was 15 nodes with temperature rise. The loss function was set to mean squared error and the model used the stochastic gradient descent method called Adam as the optimizer. In total, the model encompassed 825 parameters for the neural network. The building DT utilizes this model to forecast the consequences of altering various building energy parameters. For instance, one scenario involves assessing the temperature effects if energy consumption of the building is reduced by 20%. Another use case is predicting energy consumption fluctuations in response to changes in outdoor temperature. Leveraging this model and weather forecasts, the DT can offer accurate estimates of the energy required to maintain specific thermal comfort within the building.

E. Platform for visualisation of the DT

An interactive 3D application was created to visualize the DT, allowing users to get an overview of the sensor data and assess if they are within operating limits. Users can navigate freely through the virtual environment, observing sensors within the building and exploring their respective values. By utilizing the Unity game engine [17], the application presents a view of the building's surroundings, incorporating a low-fidelity model based on data from OpenStreetMap [18] and a photogrammetry model for the building's exterior (Fig. 3). As users approach the building in the application, it fades out to reveal interior floors and sensor data (Fig. 4). The floors are either visualised using detailed 3D models created from laser scans (Fig.4), or simple 2D floor plans (Fig. 5). The sensor values are depicted by circular icons that are color coded red, yellow or green depending on preset limits. To avoid visual clutter, a level of detail approach based on

distance is used for the sensor data visualisation. At a distance, multiple sensor values at the same location are combined into one. They are split as the user approach and textual representation is added as the user gets even closer.
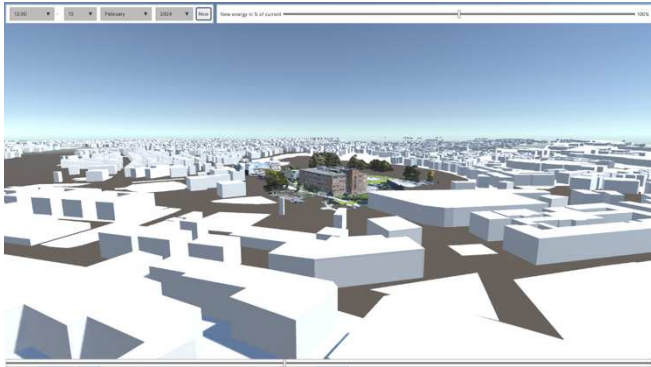

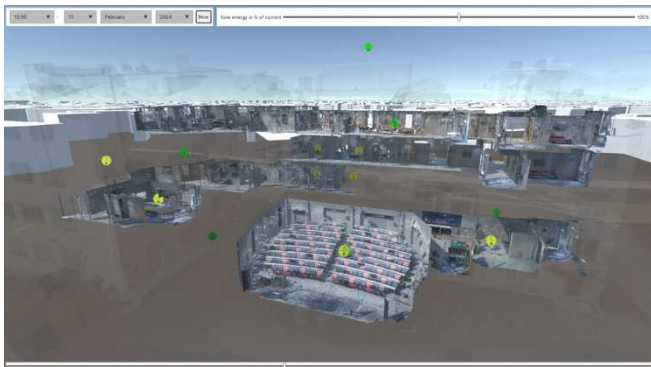Fig. 3. The building seen from the outside in the DT platform.

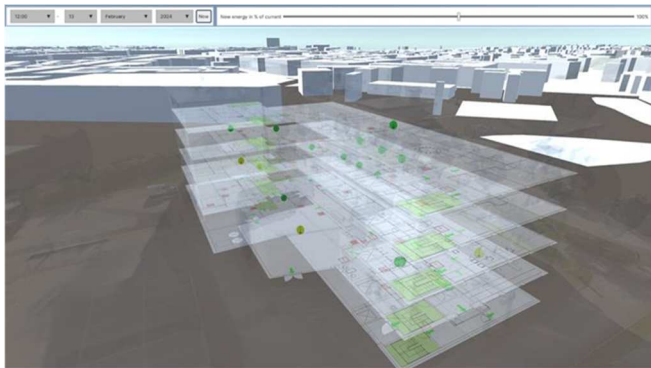Fig. 4. Interior of the building floors and sensors visualised.

Fig. 5. Interior of building visualised using floor plan

III. CASE STUDY AND FINDINGS

A. Pilot building

The developed DT and ML model framework were employed to study the energy performance of one of the office buildings of Institute for Energy Technology (IFE), located in the city of Halden, Norway. The building was constructed in 1947 with 4 floors occupied by offices, meeting rooms, a workshop, laboratories, and an auditorium. The building features a concrete and brick structure with insulated walls and windows comprising a modern centralised heating and ventilation system. As part of the smart buildings' initiative, the building is fitted with 62 IoT sensors measuring and providing real time information about the number of occupants in the building, indoor temperature, humidity, CO_2 levels at various parts of the building.

B. Energy performance study of the pilot building

Through these installed IoT sensors data were obtained and analysed to acquire detailed insights into the building's energy behaviour across different seasons throughout a 10-month monitoring period from 1/1 2023 to 31/10 2023. The energy consumption of the building for the same period was retrieved through the smart meters and energy supplier's database. Outdoor climate information was retrieved through the nearby weather station in the surrounding area.

A relevant set of operational indicators such as indoor temperature, humidity and CO_2 levels were employed with the purpose to provide information on the actual energy performance of the building to different stakeholders including the facility managers, service providers, researchers, and occupants.

Data were collected with a sampling interval of 1 hour, leading up to 6440 differing datasets for the study period. All data were normalised (range: 0-1) using the MinMaxScaler in the scikit-learn package. Then the data were shuffled and divided into a training set and a test set by using the train_test_split function in scikit-learn, the fraction for training where 2/3 and the last 1/3 were used for testing purposes. For training, noise with 0.05 stddev was added to prevent overfitting. In addition, the learning rate during training was adjusted, starting at 1e-3 down to the selected minimum value at 1e-6. The training was performed with 300 epocs and a batch size of 32. As seen from the trend in Fig. 6, the model quickly converged to a solution that fitted the validation set (10% of training data) well.
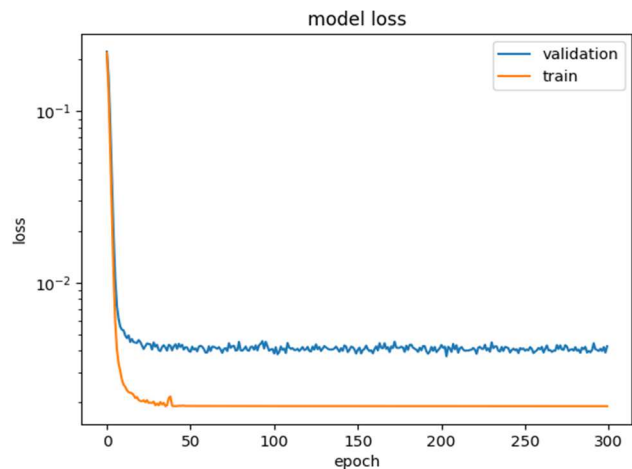

Fig. 6. Loss function development during the training process

After training, the last 1/3 of the data were used to test the model. For the different test sets we obtained a RMSE value of around 0.0028, indicating that this model behaves well for this problem. Main purpose of the model was to act as an analytical and predictive tool for the DT, where it accepts the inputs as described earlier, normalises the data (using the same fitted scaler), predicts the temperature raises and returns this back to the visualisation layer of the DT. This provides us the ability to predict the temperatures when we the energy consumption is manipulated. With this model, the facility managers can adjust the energy supplied to the building's heating system while continuously monitoring the changes in the thermal comfort of the building. For example, the heating

can be turned off/reduced in the weekends and evenings when there is no occupancy in the building. To test this, the energy consumption of the building was reduced by 20% to see what effect this would have on the indoor temperature. In Fig.7, the plot illustrates the indoor temperature predictions generated by the model following a 20% reduction in energy consumption. Presently, the building operates without any energy reduction during nighttime or weekends, resulting in excessive energy consumption. According to our model, implementing a 20% reduction in energy would yield only a slight decrease in temperature, averaging just over 2 degrees. By incorporating these predictive insights into the DT, important information could be effectively communicated with different stakeholders. For example, in the case of this building where heating and ventilation systems are managed by separate entities, facility managers could leverage the DT to convey optimal control settings for the HVAC system.
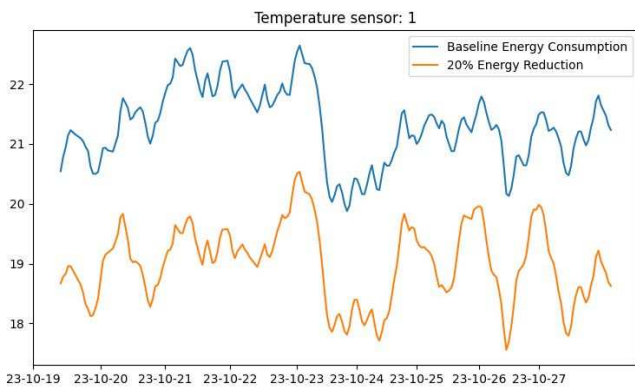

Fig. 7. Comparison of Results from the model: Baseline Energy Consumption vs. 20% Reduction Scenario

The 3D DT application enables users to analyse historical data by selecting specific dates and times, providing insights into past performance of the building. Additionally, users can leverage the ML model to assess the effects of adjusting energy levels on temperature. Fig. 8 shows an example visualisation of the depicted temperature and humidity at 100% energy level alongside a reduction of 4 degrees in temperature when energy consumption is decreased by 30%. This highlights clear opportunities for energy conservation without compromising the thermal comfort of the building.
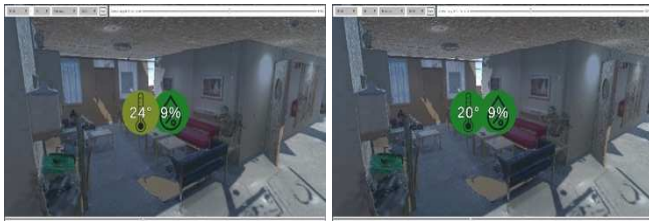

Fig. 8. (i) Temperature at 100%. (ii)Temperature after reducing energy consumption by 30%.

IV. DISCUSSION

The 3D visualisation of the DT offers the advantage of providing a quick overview of the building's thermal condition and determining whether it operates within established limits. It facilitates the identification of any deviations, existing problems, and their specific locations. However, one main challenge for the 3D visualisation is obtaining a clear view inside the building, as floors, walls, and other geometrical elements may obstruct each other and the sensor values. It is also challenging if there are areas with a high concentration of sensor values as they will occlude each other. We have tried to address this issue by dynamically adjusting transparencies and employing level of detail techniques, yet finding an optimal view could remain challenging for non-expert users of 3D navigation. To further enhance the user experience, predefined viewpoints could be offered, alleviating the need for users to navigate the visualisation manually.

Processing of data from IoT sensors presents significant challenges due to the diverse types and quantities of sensors, as well as the frequency of data collection. Since DTs rely on historical and real-time data from the sensors for reflecting the historic and current state and predict future state of the building, standardization of the IoT platform is essential for ensuring interoperability, scalability, ease of integration, and data consistency. By applying the NGSI-LD standard instantiated by FIWARE IoT agents and the FIWARE Context Broker (Fig. 9), the data stream from the various data sources will be normalised according to the selected data model and stored as JSON documents in MongoDB [19]. FIWARE make use of Smart Data Models [20] to safeguard a standarised API to access the data, even if the data in their IoT vertical have been represented according to various standards.
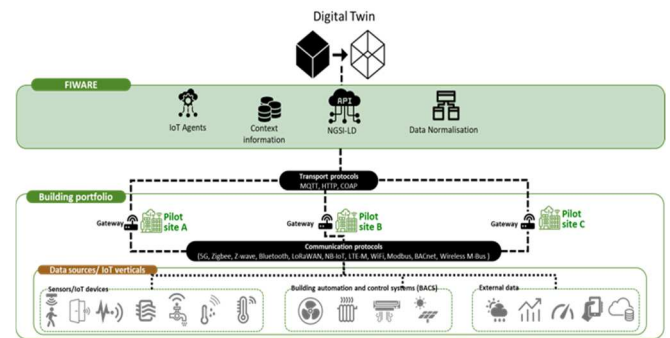

Fig. 9. Data architecture framework for the DT

Other crucial aspects to consider in the implementation of DT are the data security and privacy. IoT sensors capture highly valuable and often sensitive data, making it vital to protect the data from security breaches. Particularly when sensors inadvertently or intentionally track individuals, privacy concerns become foremost important. This warrants further research and exploration in the data security and privacy topics.

A. Limitations of the model

As the temperature control in the case study building maintained at a stable state within limits, there have been very limited fluctuations in the indoor temperature. On the other hand, outdoor temperature has exhibited many transients during the observed period. To improve the quality of the model, it would be beneficial to incorporate transient temperature variations indoors as well. Typically, such models would be solved as timeseries issues, considering the time it takes for indoor temperature adjustments, known as the time constant. However, as indoor temperature transients have not been observed, the model does not account for time constants. To enhance the model further, Long Short-Term Memory (LSTM) layers should be implemented in the model, for treating the data more as timeseries. Without time considerations, the model assumes a steady-state situation for indoor temperature.

Occupant behaviour is another critical variable in the energy performance optimisation of buildings. Thus, understanding how occupants use the building is highly valuable. The current model only considered the building occupancy and not the perceived thermal comfort of individual users. So, factors such as building occupancy, user behavior patterns, and individual preferences for thermal comfort should be included in the model in future for further enhancing the energy DT of the building.

V. CONCLUSION AND FUTURE WORK

The case study has demonstrated the application of 3D DT framework, smart sensors (IoT), real-time measurements and data-driven models for the purpose of optimising energy performance of existing, legacy buildings. The developed prototype, based on real-time monitoring, introduced a novel way to monitor the building´s energy performance and predicting future energy consumptions while providing insights into the usage patterns of the building. The case study also highlights the benefits of integrating Industry 4.0 practices with existing buildings for energy performance optimisation, while emphasizing the need for a standard architecture for collecting and sharing the data from the smart sensors. By enabling intelligent energy optimisation strategies in older buildings, the study also contributes directly and indirectly for achieving the UN sustainable development goals, especially to the goals related to responsible consumption, sustainable cities & communities and climate action[21]. Overall, the findings of this study are expected to contribute to the ongoing and future research on energy performance optimisation of buildings, by highlighting the significance of DTs and AI for this purpose.

A. Future research

As part of the case study, certain areas have been identified for potential further research. As discussed earlier in the limitations section, the model could be further improved by adding more layers and variables such as the occupant behaviour in the building. To deal with the privacy issues related to the behaviour of residents or tenants, the use of Multi-Party Computation for Federated Learning[22] could be introduced in a future case study. To bridge the gap between BIM models and the deployment of smart devices in the building, further research on the automation of extracting and creating NGSI-LD entities from e.g. an IFC file is needed. This research could be supplemented by applying the SAREF ontology extension[23] for buildings to establish the semantic relationships between NGSI-LD entities and to improve interoperability between building portfolios. The impact of enriching the data using semantics for the selected ML models could be further investigated in the future case research. Generative AI has already entered the construction industry, and a future research area could be the use of concepts like Prompt Engineering in combination with 3D visualisation techniques to gain new insights into energy efficiency and indoor climate phenomena.

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