IECON 2023- 49th Annual Conference of the IEEE Industrial Electronics Society | 979-8-3503-3182-0/23/$31.00 ©2023 IEEE | DOI: 10.1109/IECON51785.2023.10311659

Integrating Energy System Monitoring and Maintenance Services into a BIM-based Digital Twin

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***Abstract*— The digitalization process is steadily increasing in the building industry and promises new perspectives for better designing and operating buildings throughout their life cycle. However, digitalization has not yet brought its greatest benefit for tackling the rising global energy demand and is even generally associated with more energy consumption. Instead, it has become urgent to rationalize energy use and decrease energy wastes. Indeed, buildings are responsible for about one third of the global energy consumption in the world [1], and 30% of this energy is even wasted through wrong or suboptimal operation, malfunctions and energy-unaware user behavior. Technologies supporting resource saving already exist for e.g. fault detection and mitigation, optimized energy systems control or predictive maintenance. But they necessitate much manual effort by experts to be configured and deployed since every building is to some extent unique with regard to its location, equipment and usage. Moreover, they require much expert knowledge and are not adapted for a daily usage by facility managers or even building users. These measures require also many data for continuous observation, analysis and system adaptations in real time. Although modern building management systems (BMS) can generate lots of monitoring data from sensors and meters, there is still poor or no reuse of building design data already produced in preliminary stages of the building life cycles. In view of these facts, this paper proposes a new data management workflow that relies on the reuse of building design information for facility management, and that shall fasten the deployment of energy-saving services while increasing user energy awareness and engagement in reducing energy use. For that purpose, this workflow makes use of building information modeling (BIM), knowledge graphs, data analysis and web technologies in order to develop a BIM-based Digital Twin for energy saving in the building operation phase.**

Keywords*— *Building Information Modeling, Knowledge Graph, Energy Monitoring, Condition Monitoring, Digital Twin, Expert System

I. INTRODUCTION

Many data are generated during the life cycle of a building, but many of them are not sustainable and get lost because of lack of digital processes and data transfers. Indeed, even if huge amounts of data are produced during the design and operation phases of a building, there is still poor reuse of its design data in its operation phase. During building operation, building management systems (BMS) are usually responsible for collecting data about a building, some of which relate to its energy usage and performance. BMS data are obtained via sensors and meters, which provide information about for example the operating states of technical systems, the indoor temperature in rooms or energy consumption. Due to its strong time dependency, this information can be categorized as dynamic data about a building.

In addition, there exist many static data created since design phases with the support of the BIM (Building Information Modeling) method [2]. However, there is no systematic reuse of the accumulated BIM information during building operation. This information describes the building and its technical systems including their components, their technical characteristics and their layout in the building. Despite the multiple kinds of information that BIM offers, there is still a large information gap between the design phase and the operational phase. In practice, there is no leveraging of BIM design information during the operational phase. Even if a lot of information is captured during the design phase of a building and high quality CAD models are relied upon, the digital transfer of all created information to the actors and systems of the operational phase is either poor or non-existent. On the contrary, information transfer is still paper-based or based on human-readable digital documents like drawings, but not machine-readable or even less machine-interpretable.

It is generally accepted that software systems embedded in building control systems or developed for computer-aided facility management (CAFM) could benefit from such an information repository [3], but in practice they still rely on well-defined and proprietary data models [4]. In view of that, digitalization can become a great support for deploying monitoring services, operating buildings more efficiently and providing better guidance to users with the aim of saving energy. One main promise of digitalization is making data reusable and sustainable over the building life cycle, so that digital services can leverage their value for faster and more intelligent facility management processes.

In view of this information gap between building design and operation, a workflow and software tools based on the reuse of BIM data during building operation were developed. In this context, a process of information integration and semantic enrichment was first formalized as a BIM workflow. In addition, use cases were defined and software components were developed that focus on energy system monitoring and predictive maintenance with the aim of saving energy.

II. BIM Workflow for Facility Management

The main intent of the presented workflow is to automate the deployment of data analysis services in buildings by reusing their design data. Even if a fully automatic system has not been reached in the current prototype so far, we tried to maximize the reuse of BIM information.

An important step in the reuse of design information is the linking of building data from CAD design with operational data, so that the BIM model does not remain a static representation of a building system, but becomes a dynamic information model. This still requires some manual effort to link the BIM elements with sensors objects from the database storing measurements time series. By using the globally unique identifiers (GUID) from the open BIM format IFC (Industry Foundation Classes) [5] as association keys, it is possible to make explicit associations between static and dynamic data.

Subsequently, the IFC model is converted into an ontology using an existing converter [6]. The use of ontology makes it possible to semantically enrich the building model in further steps. The resulting semantic representation of the building is presented in following section and mainly consists of an aggregation of ontologies used either for system description or for knowledge representation. That latter kind formalizes the knowledge of an energy expert who would setup a monitoring system for a specific building by relying on its design.

In practice, this knowledge is generic and can be reused for any building. Using this knowledge and the building data as input, an inference engine performs a metadata analysis to characterize the building energy system, as an expert would do by reading technical drawings, and select applicable data analysis functions for energy system monitoring and maintenance.

To summarize, this workflow is illustrated in Fig. 1 and includes the following main parts:

- a BIM model gained from the design phase of a building.
- the operational data of the building, which is recorded and managed in a database.
- an integration of the BIM model with operational data realized inside a semantic model describing the whole building energy system and assigning data points to building elements for representing a dynamic BIM model.
- a knowledge base and an inference engine for metadata analysis to characterize the building, select proper data analysis functions and provide them with the right data as inputs.
- data analysis functions of two kinds:
    - for energy system monitoring by assessing operational data to identify energy waste and suggest corrective actions,
    - for condition monitoring by evaluating operation data at component level using wear models to assess the health of single components and identify maintenance needs for condition monitoring.

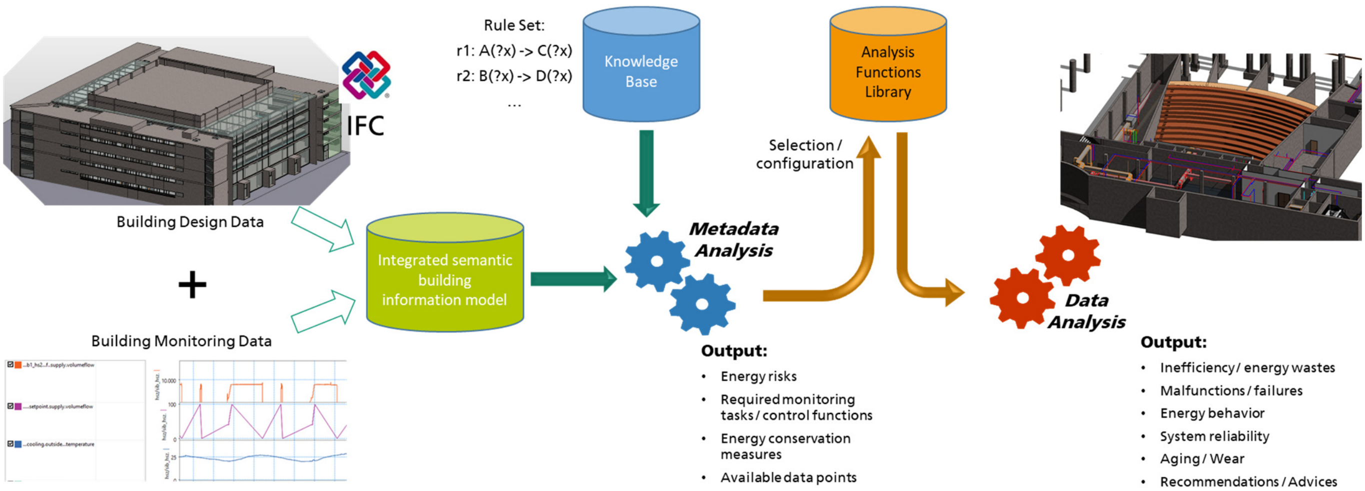

Fig. 1. BIM4FM workflow for automated monitoring system configuration and execution

III. Data Integration and Knowledge Modeling

The semantic model is composed of ontologies which conceptualize the domains of building energy systems and automation. In the field, several metadata schemas have emerged and are for a part reused in the ontology system. These include ifcOWL that was released by buildingSmart as an OWL (Web Ontology Language) representation of IFC [5]. The automation domain was formally described into SSN/SOSA [7] and CTRLont [8]. The Brick ontology [9] has emerged a few years ago for representing HVAC systems. The Building Topology Ontology (BOT) is a lightweight ontology for describing the spatial structure of buildings [10], and the QUDT ontologies were initiated by the Constellation Program at NASA [11].

As each ontology covers a specific domain with its limitations, we developed further ontologies [12] which enable a full description of a building in its operation phase and at metadata level (see Fig. 2). Additional ontologies consist of the Energy System Information Model (ESIM) which describes the built-in energy system like Brick but fills some concepts gaps. The Metric model consists of a set of quantities that complement QUDT and SSN/SOSA with specific metrics for HVAC (Heating, Ventilation and Air Conditioning). The Risk model provides a catalogue of possible faults and operation errors that can lead to energy wastes, together with corrective energy conservation measures. The BAF (Building Automation Functions) model is a catalogue of generic control functions usually used by automation engineers. Finally, the Sense ontology represents the central knowledge model that aggregates all the concepts, and in which logical axioms and rules are encoded for formalizing expert knowledge. This contrasts with the other ontologies that focus on system description while the Sense ontology aims at emulating the process of BMS setup by characterizing the system and prescribing applicable monitoring functions. Fig. 3 represents some of the fundamental concepts composing the Sense ontology that share causal relationships to support the setup of BMS functions for e.g. fault detection. More generally, when processed by an inference engine or reasoner, the Sense model enables to classify locations within a building, and to characterize its topology and built-in systems in order to select and configure relevant monitoring functions.

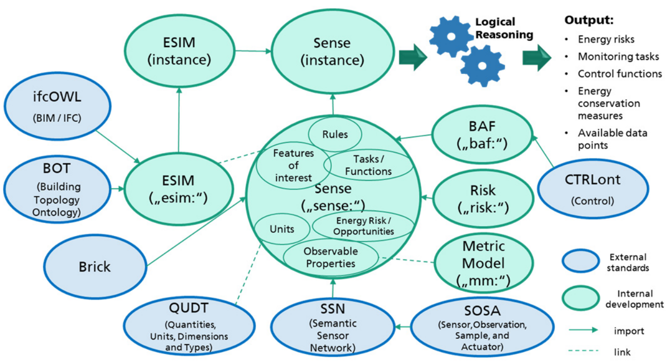

Fig. 2. Ontologies composing the integrated semantic model

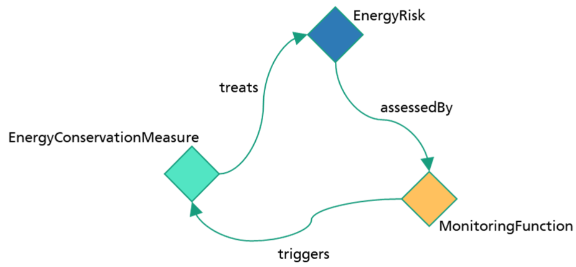

Fig. 3. Some concepts and relationships for configuring fault detection

This inference process is referred to as metadata processing in Fig. 1. It selects e.g. thermal zones by checking if they host some distribution component like e.g. radiators from a heating system. More concretely, if a room hosts radiators, it will be classified as a heating zone and considered for checking potential overheating. If a sensor exists for measuring the temperature in this room, the sensor ID and information about the location of interest will be passed to a function that monitors overheating. In the data analysis step from Fig. 1, this function will then provide as output the end user with the advice to reduce indoor temperature if overheating really occurs. For enabling this kind of inferencing, the Sense ontology incorporates rules and logical axioms like the one given as example in Table 1 (A1) for classifying heating zones. For simplicity reason, the axiom is written in the so-called Manchester syntax which provides a human-readable description of OWL statements.

Some axioms are also used for classifying data points from the BMS system relying on the topological and functional description of the energy system. Thus, a data point of a valve position or command can be classified as a "heating coil valve position" by interpreting the function of its related object (e.g. heating coil) inside the fluid flow. The corresponding axiom is written in Table 1 (A2). This precise data point classification step is useful for the system to be able to pass the right data as input to monitoring functions that specifically require valve positions of heating coils. Such functions can be used for e.g. checking if air heating is activated whilst an air handling unit (AHU) is in cooling mode.

Further rules are used to select all entities that should be monitored for some fault detection if they are threatened by some energy risk. In that case, potential risks can be identified in an AHU according to its built-in components (e.g. heating coil, cooling coil, fans, humidifier, air filters…). As a result of the metadata analysis step, specific monitoring functions get associated to corresponding existing instances of AHUs inside the ontology. Accordingly, if an AHU carries a certain energy risk, the inference engine will select corresponding monitoring functions in order to identify related faults or issues from real operation data. Some rules are listed as examples in Table 1 (R1, R2).

Similarly, if air filters compose an AHU, and differential pressure data points are available inside the BMS database, the system can then associate relevant condition monitoring functions to these objects. Section IV.B describes one condition monitoring algorithm specifically implemented in the research prototype of this paper.

TABLE I. SOME AXIOMS AND RULES INSIDE SENSE

id	Definition in human-readable notation
A1	Class: esim:HeatingZone EquivalentTo: esim:SpatialStructureElement and (esim:hosts some (esim:EnergyDistribution and (esim:composes some esim:HeatingSystem)))
A2	Class: mm:HeatingCoilValvePosition EquivalentTo: brick:Point and (brick:isPointOf some (brick:Valve and (brick:feeds some brick:Heating_Coil))) SubClassOf: mm:ValvePosition
R1	brick:AHU(?ahu) ∧ brick:Heating_Coil(?hc) ∧ brick:Cooling_Coil(?cc) ∧ brick:hasPart(?ahu, ?hc) ∧ brick:hasPart(?ahu, ?cc) → risk:hasRisk(?ahu, risk:SimultaneousAirHeatingAndAirCooling)
R2	Risk:Risk(?ri) ∧ sense:MonitoringFunction(?mf) ∧ risk:hasRisk(?e, ?ri) ∧ risk:assessedBy(?ri, ?mf) ∧ → sense:hasFunction(?e, ?mf)

IV. ENERGY SERVICES

A. Energy System Monitoring

At this stage, monitoring functions selected in the previous inference step, i.e. during metadata processing, are executed in parallel. They compose all together our energy system monitoring service. The selected monitoring functions are executed continuously and in real time. They consist in our case of data analysis scripts that are coded in Python language and that query the BMS data selected from the inference engine. They are used for interpreting the operational conditions of the building technical systems (weather conditions, systems on/off status, indoor conditions, etc.). They are based on command and measurement time series which are continuously synchronized from the BMS into local SQL databases. If the service identifies faults, energy wastes or energy conservation measures, some warnings or recommendations are generated as output.

The appropriate energy-saving recommendations are based on available heating and cooling zones identified by the inference engine, as well as available data points to verify potential energy waste related to heating, cooling, lighting, or equipment use. The system is composed of monitoring functions which suggest the following types of energy conservation measures in real time:

- avoiding overheating or undercooling by changing temperature set points.
- increasing the natural solar heat gain (heating season) or decreasing it (cooling season) by opening/closing the blinds.
- lowering or turning off heating/cooling in unoccupied rooms.
- reducing thermal energy losses through openings by closing windows.
- detecting wrong operation or failures (e.g. defective sensors) in the HVAC system that cause energy waste.
- saving lighting energy by providing more natural light or turning off lights in unoccupied rooms.

B. Condition Monitoring

Additionally, a condition monitoring service was implemented [13] which evaluates operation data using a wear model to assess the reliability of certain HVAC components such as air filters of air handling units, and to identify possible maintenance needs. State of the art condition monitoring systems for air filters in ventilation systems consider that the system is operated at nominal volume flow. But for optimal air conditioning of buildings, it is necessary to adjust the volumetric flow of supply and exhaust air depending on the prevailing boundary conditions (e.g. weather) and the use of the building. Therefore, by HVAC systems with variable volume flow, the previous assumption is only fulfilled in one operating point. Outside this operating point, existing condition monitoring systems assess the air filter condition in a too optimistic manner. Therefore, polluted air filters remain undetected until their regular check, leading to higher energy consumption. If the true condition of an air filter is known, it could be changed before it is clogged. So, a condition monitoring service was developed for the case of HVAC systems with variable volume flow.

The clogging of an air filter can basically be described via the differential pressure across the air filter (Δp) [14]. A model was applied that integrates the volume flow through the air filter ($\dot{V}$), the air density (ρ), the dynamic viscosity of the air (μ) and the resistance coefficient (c). The model is described in Equation (1) which makes it possible to estimate current clogging of air filters based on data history.

$$\Delta p = c \cdot \mu^{2-n} \cdot \rho^{n-1} \cdot \dot{V}^{n} \qquad (1)$$

For the condition monitoring of the air filters, the data of last seven days are used to train the model. Then the theoretical differential pressure at nominal flow rate is calculated with the trained model and compared with a differential pressure limit. If the calculated differential pressure at nominal volume flow exceeds the limit value, the air filter is worn and must be replaced. Accordingly, notifications about the actual clogging state of air filters are periodically produced by the service.

V. DIGITAL TWIN

Both the energy system monitoring service from Section IV.A and the condition monitoring service from Section IV.B have been integrated into a so-called Digital Twin platform which consists of a web application that renders the BIM model in 3D and incorporates additional visual components. A user, i.e. a facility manager or building owner/user, can then check different operating conditions in a building and take actions to save energy. Corresponding software components presented in previous sections compose the full BIM4FM workflow. These are displayed in Fig. 4 as components of a layer-based software architecture. The BMS data from the lowest layer were imported either through an OPC UA (Open Platform Communications Unified Architecture) interface [15] or a REST (REpresentational State Transfer) API [16] depending of the capabilities of the legacy BMS. Both data analysis services are deployed as web services which regularly send their output data to the Digital Twin user interface (UI) as JSON payloads (JavaScript Object Notation) using a REST web interface.

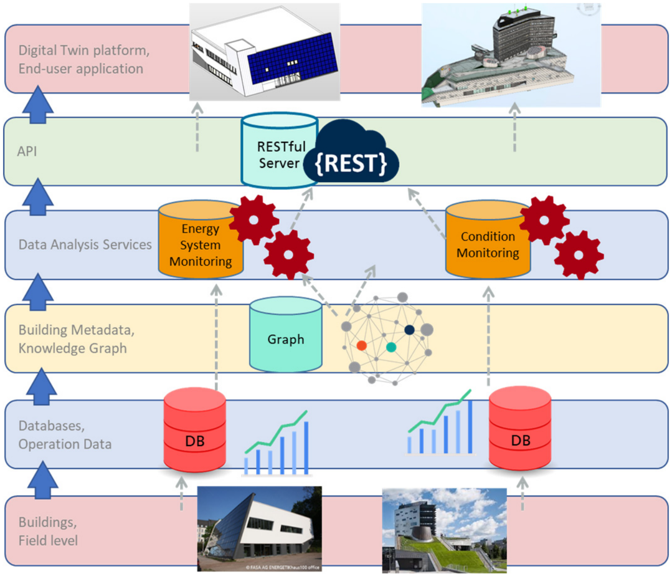

Fig. 4. Layered software architecture

The output data of both monitoring services are posted to a RESTful server and consist of the following:

- a message or recommendation expressed in natural language, describing a condition or an action that an end user could take to save energy (e.g. change of temperature set point, or filter clogging condition).
- a location in the building to which this recommendation applies (room, zone, or subsystem)
- a timestamp when the recommendation was triggered and became valid
- a validity period during which it remains valid and during which the front-end app continues to display it
- the intended effect i.e. potential energy saving related to the action described in the recommendation.

This set of information stems for a part from the data analysis results, and for another part from the data integration steps which allow to allocate data points and data analysis functions to corresponding building elements from the BIM model. As a result, real-time recommendations and warnings can be generated and unambiguously associated to specific BIM elements.

An example visualization of the recommendations view inside the Digital Twin platform is shown in Fig. 5. In that case, the Digital Twin consists of a modern two-story office building located in Germany and equipped with a solar thermal collector. The solar heat is stored in a hot water tank, located approximately in the middle of the building, which supplies heat to floor heating circuits. In summer time, an adsorption chiller is powered to inject cool water in the circuits. In Fig. 5, the spaces of the first floor are filtered and displayed in the Digital Twin UI. The energy monitoring service provides recommendations in text form to the end user through the recommendations pane on the left. In the view, the system proposes changes in temperature set points in different rooms to avoid undercooling. For that purpose, underlying data analysis algorithms process real-time sensors data from the building. For the communication between the Digital Twin and the real building, an OPC UA interface was used. It allows the energy monitoring service to collect real-time data from the local database of the existing BMS installed in the real building.

Another building, respectively Digital Twin, was implemented for a university building situated in Finland. The total area of the building is 15,100 m² distributed on 9 floors. Heating and cooling are performed by mechanical ventilation and 560 solar photovoltaic panels, mounted on façades between the rows of windows, cover part of the electricity needs of the building. BIM models of the architectural and mechanical designs were gathered. The operational data of the building was collected through the specific REST API of the installed BMS system. For that building, a focus was set on condition monitoring for the air filters of the several AHUs that compose the ventilation system. For that purpose, the data points of the BMS were associated with the BIM model using the approach described in Chapter II. They were analyzed by the data analysis algorithm presented in Section IV.B. The results of the data analyis were then transmitted to the Digital Twin UI using the specifically developed REST interface depicted in Fig. 4. The final prototype integrating the condition monitoring service into the Digital Twin is shown in Fig. 6. The service was used to analyze the clogging state of the distinct air filters in the 4 AHUs of the ventilation system. For each AHU, both filters, respectively from the air supply ductwork and from the air return ductwork, were monitored. To this end, the differential pressure data points of the respective locations inside the ductworks were used. The recommendations pane of the Digital Twin notifies every day about the current wear status of the filters. In addition, the underlying measurements data can be visualized in a plot view which can be toggled by need for each filter.

For both buildings, access to the Digital Twin platform was given to the respective facility managers of the buildings. That way, they could use the tools from their web browsers. They were ask to interact with the Digital Twin over a period of around one year. After this period, their feedbacks were in general positive. The 3D view made the tool quite appealing to use and helped locate issues in their buildings that would in general not be noticed otherwise. The impact of the Digital Twin platform in terms of energy saving could not be assessed in that experiment. A prior prototype version, without BIM integration but implementing same kinds of recommendations had been evaluated in 12 buildings in a former experiment [17]. This experiment reported an overall energy saving potential of around 12,2 % when users followed recommendations. The prototype Digital Twin platform presented in this work was developed as further extension. On the one hand it was made to demonstrate the potential of integrating knowledge graphs to automate the setup process of monitoring services by reusing building design information. This shall fasten the deployment and systematize the use of such energy services in any building, and thus enable energy saving at a larger scale. On the other hand, the BIM integration allows for better data management, the localization of issues and better user experience to increase awareness and engagement of building users to save energy.

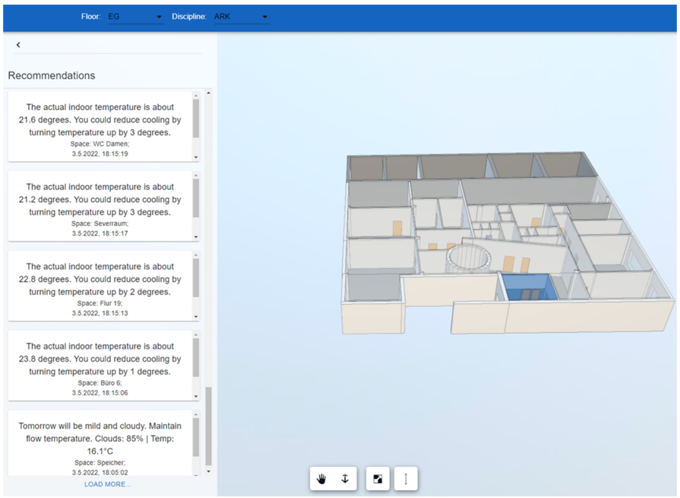

Fig. 5. Recommendations view inside the Digital Twin UI

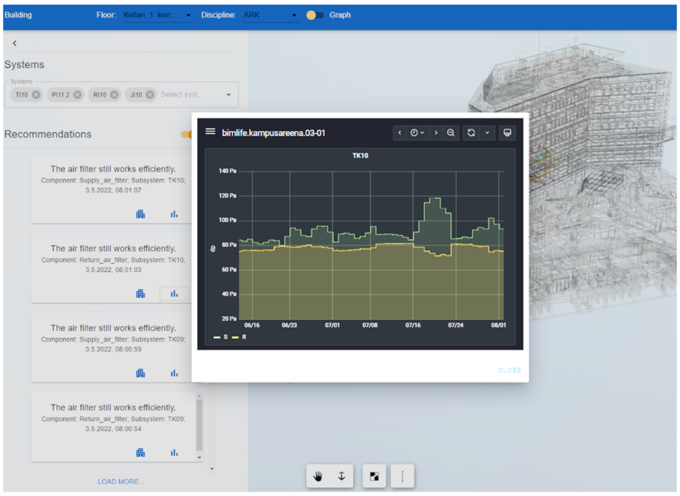

Fig. 6. Plot view of the differential pressure by two filters of one selected AHU inside the Digital Twin. Green: supply duct; Yellow: return duct.

VI. Conclusion

The presented Digital Twin framework has been developed as a research prototype in 2 pilots with different levels of maturity. As a result, a Digital Twin platform has emerged that embeds energy system monitoring and condition monitoring as facility management services in a BIM environment. The knowledge graph and inferencing method were applied for only a few monitoring functions as proof of concept. It shows that monitoring functions can be automatically selected and configured from an ontological description of a building and its sensors system. Nevertheless, the workflow still necessitates much manual effort to integrate sensors data with the BIM model, and to create the ontology system. Further works are investigating how to automate this process by integrating machine learning technics.

Acknowledgment

This work was enabled by the Finnish-German project BIMLIFE (03ET1569) and the German project N5GEH-SKAMO (03EN1060B) thanks to the generous support of the German Federal Ministry for Economic Affairs and Climate Action as well as of Business Finland.

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