Optimizing Building Energy Systems through BIM-enabled georeferenced Digital Twins

Christoph Blut[a], Ralf Becker[a], Tristan Kinnen[a], Dominik Schluetter[b], Christoph Emunds[b], Jérôme Frisch[b], Dirk Heidermann[c], Matthias Wenthe[d], Tobias Rettig[e], Marc Baranski[e], Christoph van Treeck[b], Joerg Blankenbach[a]

[a]Geodetic Institute and Chair for Computing in Civil Engineering & GIS, RWTH Aachen University, Germany
[b]Institute of Energy Efficiency and Sustainable Building E3D, RWTH Aachen University, Germany
[c]TEMA Technologie Marketing AG, Germany
[d]IMS – Internet Marketing Services GmbH, Germany
[e]aedifion GmbH, Germany
E-Mail: [blut, becker, kinnen, blankenbach]@gia.rwth-aachen.de, [schluetter, emunds, frisch, treeck]@e3d.rwth-aachen.de, heidermann@tema.de, wenthe@ims.de, [trettig, mbaranski]@aedifion.com

Keywords: Digital Twin, BIM, Technical Building Equipment, AI, VR and Geospatial AR.

Abstract

Building energy system management is critical for resource-saving approaches amid climate change-driven energy transitions. This paper presents a digital twin toolchain leveraging modern technologies such as Building Information Modeling (BIM), Artificial Intelligence (AI), Virtual Reality (VR), and Augmented Reality (AR). The toolchain automates the derivation of georeferenced digital twins during Technical Building Equipment (TBE) commissioning. Using a Scan vs. BIM process, discrepancies between as-planned and as-built TBE are identified, allowing automatic updates to the BIM model. Validation methods ensure both physical and functional aspects of the TBE are accurate. VR and AR facilitate off- and on-site commissioning, enabling immersive visualization and live sensor data access. An evaluation in small and large-scale demonstrators shows the toolchain's scalability and efficiency, with promising results in performance and accuracy. Future work aims to integrate more operational data, enhancing the digital twin's capabilities for building energy system management.

1. Introduction

Building technology is becoming increasingly complex. This applies in particular in times when a resource-saving approach is required to implement the energy transition triggered by climate change. An important task of taking a building into operation is the commissioning of the Technical Building Equipment (TBE) after completion of the construction, for example to identify possible deviations compared to the plans, requiring adjustments of the TBE. Though, due to the complexity of the TBE, commissioning as well as operation of TBE are becoming gradually more difficult.

A promising solution are Building Information Modeling (BIM)-based digital building and TBE models which can be applied starting in the planning phase through commissioning to the operational phase to transform them into a digital shadow of the physical existing situation. By including sensor data and BIM-based simulations to improve TBE design and control, the shadow can be further enhanced into a digital twin. To obtain a digital twin, it is key to find deviations between the planning data and the built situation, which can be achieved efficiently during commissioning of the building and should be continued later during operation. In the nationally funded project energyTWIN, we developed a toolchain to (automatically) derive georeferenced digitals twins during the commissioning phase of TBE using an as-planned vs. as-built process and for enhancing commissioning of TBE through BIM-enabled automation. This paper shows some of the developments realized in the project.

Followed by the introduction, section 2 presents the developed thermal capturing system, a cost-effective tool to acquire color and thermal point clouds of the built situation (as-built) that reflect the physical properties of the TBE. Section 3 describes our solution for capturing operational data of the TBE to validate its functionality. Both systems can make significant contributions to obtaining knowledge about the installed TBE for commissioning and operation. Next step, shown in section 4, is to compare the built TBE to the planning data (as-planned) to identify any deviations that require updating to transfer the as-planned model to an as-built model for the operational phase of the building. Section 5 describes the methods to automatically find relationships between the TBE components that are essential for understanding and evaluating their functionality. The methods to manage and provide all these heterogenous data to the different applications, are shown in section 6. Section 7 presents commissioning enhancements of TBE using Virtual Reality (VR) and Augmented Reality (AR). Finally, section 8 describes the evaluation processes in two selected demonstrators.

2. Capturing Thermal Reality

Capturing the built situation should be as flexible and user-friendly as possible and the system should be capable of capturing various types of information concerning TBE. Geometric information, visual data such as surface color, and thermal properties, can help ensure the correct system functionality during commissioning and operation and identify potential energy savings. The geometry of an object contains essential information related to its size and shape, while the color can provide valuable insights into its material, surface characteristics and object type. Thermal data, on the other hand, can provide important information about the surface temperature and hints concerning possible energy consumption patterns of the TBE, which can verify as-planned commissioning and are crucial for optimizing its energy efficiency. By capturing comprehensive information about a building's TBE, energy analysts can gain a deeper understanding of its energy consumption and recognize opportunities for improving energy efficiency.

For the parallel acquisition of geometric, color (RGB), and thermographic data, we developed a combined system consisting of a FLIR ADK[1] thermal camera mounted to a Microsoft HoloLens 2[2] (MHL2) to generate RGB and thermographic point clouds simultaneously, as shown by (Becker et al., 2022). The MHL2 is a head-mounted mobile mixed reality (MR) system that contains a range of built-in sensors, including a depth camera and a RGB camera. The MHL2's head-worn design offers greater flexibility and faster capturing speeds, than for instance terrestrial laser scanning. Additionally, with its MR capabilities, the MHL2 can be used both as a data capturing and visualization system, making it a versatile tool for achieving the project goals.

For combining the various data, a calibration of the sensors is necessary. For this, we employ the RGB camera of the MHL2, which is already calibrated to the depth camera. Since the RGB and thermal camera both provide images, the calibration can be achieved using visual information, i.e., with corresponding features (Mühlich and Aach, 2007), which are unique points or parts that can be identified in both images. To determine corresponding feature points easily and robustly, typically, black and white checkerboard patterns, for example printed on cardboard, are used (Placht et al., 2014). However, these types of checkerboards are unsuitable for thermal cameras because the checkered pattern is hardly or not visible at all in the thermal images, due to the low heat signature of the cardboard. As exemplified in (Lagüela, 2011) and (Ellmauthaler et al., 2013), heat-radiating light bulbs can be used as alternative, which are clearly visible as reference points in the thermal image and, thus, can be used as feature points. Therefore, we adapted this approach and developed a 3D calibration setup constructed from wooden boards with light bulbs inserted in regular intervals and uniquely identifiable markers placed on the front side in such a way that the light bulbs are located in their respective centers. For a calibration, the centers of the markers are derived from the RGB images, and the corresponding points are determined in the thermal images using the light bulbs. Figure 1 illustrates the identified center points from the RGB and thermal images.

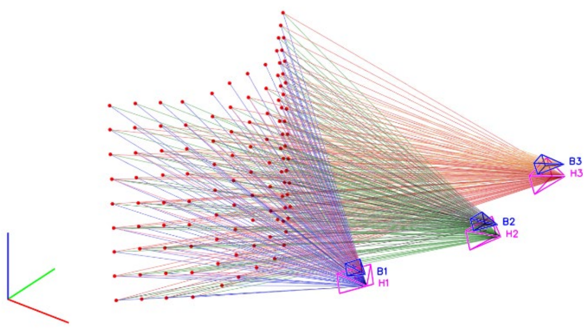

Figure 1. Found feature points within the RGB images of the MHL2 (H) and the thermal images from the external thermal camera (B) from three different viewpoints as part of the calibration process.

Once the calibration parameters for the RGB and thermal camera are identified, both cameras are co-registered. Finally, the RGB and thermal images can be projected on to the point cloud which is derived from the depth camera to obtain a RGB and thermographic point cloud as described in (Kinnen et al., 2023). An example for a thermal point cloud is shown in Figure 2.

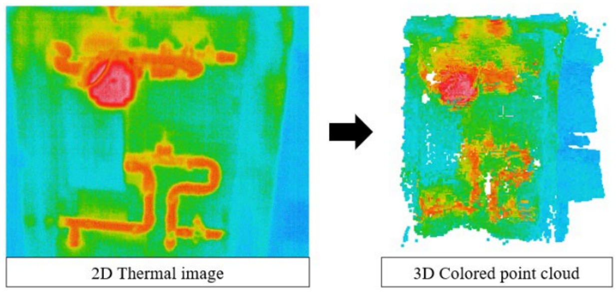

Figure 2. Exemplary comparison of a 2D thermal image and the corresponding section of a colored 3D point cloud.

3. Capturing Operational Data

While modeling the as-built geometry of the TBE tries to capture the actual physical properties that might deviate from the as-planned model, for commissioning and operation it is also necessary to validate the functional aspects for TBE and Building Services Systems (BSS).

For this, we implement a two-tier approach: (1) for the planning side, the resulting systems are analyzed from BIM data and (2) for the as-built view, data is interpreted from the building automation field level. These two data points can then be matched on a component level to assess the functionality. The as-built BIM model can also benefit from this analysis, as the data from functional aspects of the design are able to support existing information from the scan-to-BIM process via information fusion.

Using BIM data in the Industry Foundation Classes (IFC) format as input, an initial interconnected graph of BSS is generated. To facilitate this, we adapted the formal description within the TUBES System Ontology (TSO) and linked data technologies. Besides the hierarchy of systems and components shown in Figure 3, this also integrates the concept of operational states and the possible exchange of matter, energy or data through the connections found in these systems (cf. Figure 4). The resulting directed graph is converted to the Resource Description Framework (RDF) and retained in an Apache Jena/Fuseki[3] triplestore, which can be queried with standardized SPARQL Protocol and RDF Query Language (SPARQL) statements. We provide a backend module with a Representational State Transfer (REST) based application programming interface (API) to serve information on the topological setup of BSS and the respective connections. By using the topological information, it is possible to infer properties of a component within the system. The next sensor component upstream or downstream can always be found with a simple graph traversal, which translates into a SPARQL query – or as it is encapsulated already in the backend – with a call to the REST API.

[1] https://www.flir.com/products/adk/
[2] https://www.microsoft.com/en-us/hololens/buy
[3] https://jena.apache.org/

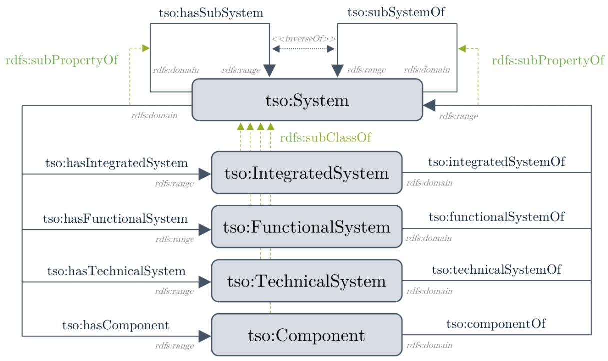

Figure 3. Building Services Systems Hierarchy in TSO (Pauen, 2022).

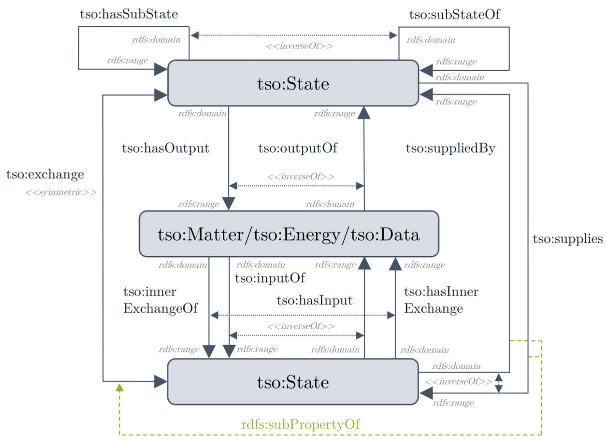

Figure 4. TSO description of matter, energy or data exchange depending on the current operational state (Pauen, 2022).

Operational data is captured centrally from different building automation services. These data points are stored locally and can be queried with a REST API integrated into the central cloud-based data management. In addition to the resulting values, metadata is generated, this encompasses the physical quantity and (SI-)unit. Within the system, further analysis is prepared to classify and cluster these data points. Using machine learning tools, probabilities for the medium flowing in a connection or pipe are calculated, as well as possible local distances (e.g., are these datapoints from one component or did they originate in different spatial contexts).

With this setup, a component like a pipe from the BIM model can be selected and queried for

1. the intended medium, the system and subsystem it belongs to and the position within this system using the topology API provided by TSO.
2. the operational data (e.g., temperature), the probable medium used and a suggestion for a cluster that might describe a component.

Comparing these data sets, the functional layer of the planning data can be validated. It can be extended, if the setpoints and boundary conditions from the planning stage are also documented together with in the building automation data points.

During commissioning of the building or for initial assessment of operational properties, additional mobile sensors might be used. These should be placed in the system using the Reference Designation Key (RDK). These supplementary data points can then be used with the other data in the frontend application to highlight specific problems arising during building operation.

Additional information, such as component types, can be derived from a QR code that each element carries (Figure 5). QR codes of different sizes (3 x 3 cm, 6 x 6 cm, and 10 x 10 cm) were used and attached to the components in the demonstrators (chapter 8). For an initial practical test, the 6 x 6 cm QR codes were utilized. The codes store eight-digit identifiers, which are inserted as an additional attribute in the content server. These QR codes can either be read using an app and linked to the database (chapter 6) with the identifier or they can contain an URL directly. In this case, these must be 10 x 10 cm in size, which is some cases makes it more difficult to attach them to components on site.

Figure 5. Combination of points of interest and QR codes.

4. AI-based As-built/As-planned Comparison

In BIM, continuous comparison between the planning data (as-planned) and the actual built situation (as-built) is imperative for new constructions projects (Arayici, 2012). Given the substantial data volumes inherent in complex TBE structures, leveraging Artificial Intelligence (AI)-based automated methods offers significant promise for efficient resolution of this challenge.

Current research is actively exploring automated approaches for comparing as-planned and as-built data. For instance, (Chen and Cho, 2018) employ a column-detection algorithm and the Random Sample Consensus (RANSAC) method to register point clouds to a BIM model, followed by a conversion of the BIM model to a point cloud to facilitate point-to-point comparison. Conversely, (Bosché et al., 2015) focus on comparing planning and real data pertaining to cylindrical objects, such as pipes, and propose a methodology for as-built modeling utilizing a Hough transformation. (Gumhold et al., 2001) adopt a corner and edge detection approach, analyzing local point densities and neighbourhood relationships for comparison purposes. In contrast, (Lee et al., 2013) present a method based on skeletonization of object representations within the as-built point cloud.

For our approaches, we also initially register the captured as-built point cloud to the as-planned BIM model and then generate a point cloud from the as-planned model. Thus, the as-planned and as-built data are then available in a common coordinate system. Following this, we focus on a component-specific analysis. With this approach, it is possible to identify whether each component of a TBE system has been built according to the planning data. More specifically, each component can be classified into one of three categories: The first two categories differ in whether a component of the planning model has been built or not. In case the component has been built, it can be additionally distinguished whether it is rotated and/or displaced in comparison to the planning data. The third category represents a false component. This could be the case for a completely different component, such as a pipe instead of a pump, or a functionally identical component with different dimensions, such as a pump from another manufacturer. The described methodology is schematically shown in Figure 6.

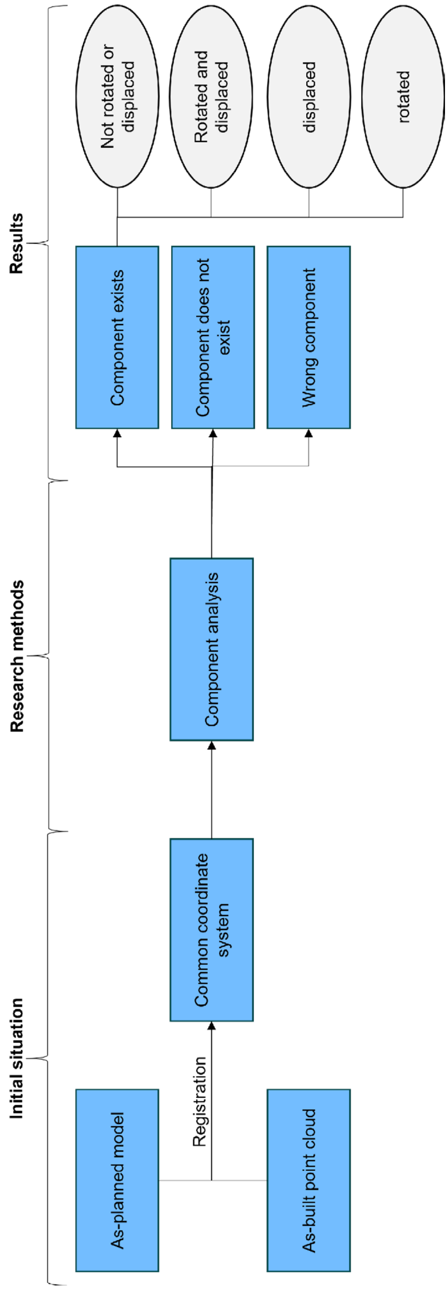

Figure 6. Schematic representation of the methodological approaches.

For categorizing the individual components, we explored different approaches:
First, we investigated methods based on known geometric data from the as-planned BIM model. Assuming registration of the as-planned model and the as-built data, geometric data at component locations served as the starting point for analyzing the as-built condition. To achieve this, the planning and as-built data is initially converted into a common format by transforming the planning model into a point cloud. Then, in a two-stage co-registration process based on RANSAC and ICP, cumulative transformation matrices are determined for component extracts from both point clouds. These matrices facilitate as-built modeling if the component is recognized. Recognition is aided by downscaling component extracts into voxel structures and examining overlaps of resulting voxel grids. For this purpose, the medians of the distances of all previously assigned point pairs determined in the initial lengths are adapted as voxel sizes.

In a second approach, we investigated component-specific differences between planned and actual states based solely on geometric properties, without prior knowledge. This included machine learning and deep learning approaches, such as sparse convolutional neural networks (Graham and van der Maaten, 2017) trained to classify TBE components based on their point cloud representations. Additionally, the as-planned model as well as the as-built point cloud are holistically transformed into a grid of uniform voxels, with occupied voxels determined using ray casting along the trajectory of the mobile capturing process. The resulting occupied grids for the as-planned and as-built data are then aligned with each other to identify areas of deviation.

Based on the results of the different approaches, a BIM model and a colored point clouds are created. These point clouds clearly indicate by color which components of the TBE system were realized according to the planning data and which deviate from it. The results can for example be transferred to AR or VR to identify deviations quickly and reliably during inspection. An illustration of this is shown in the Figure 7.

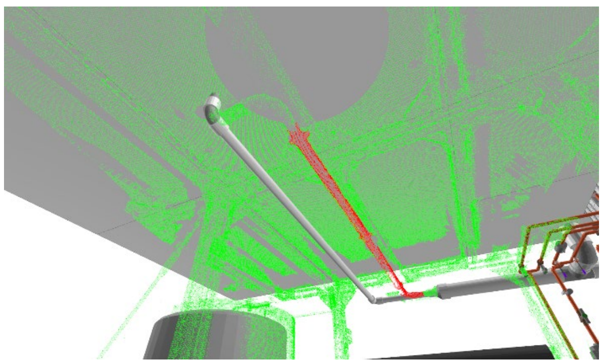

Figure 7. Exemplary result visualization using colored point clouds of Viega Cube Aachen (Viega GmbH & Co. KG)

We found that the best results could be achieved by combining all the investigated methods, since each has strengths and weaknesses.

5. Analyzing TBE Relationships

An important aspect of the TBE commissioning process consists of checking the correctness of the connections between individual components. BIM offers the capability to model these connections in a semantically meaningful way. However, due to interoperability issues between different BIM software products, this information can get lost and might need to be reconstructed (Bazjanac and Kiviniemi, 2007). Another example in which connectivity information needs to be inferred is that of deriving a BIM model from point cloud data (Scan-to-BIM). In this case, no information about connections is known a priori and the topology of the TBE system needs to be inferred.

In our approach, we represent the TBE system as a graph with vertices for the BIM components and edges for the connections between them. We trained a Graph Convolutional Network (GCN) (Kipf and Welling, 2016; Schlichtkrull et al., 2017) to predict missing edges in the graph. GCNs have shown promising results in several applications involving graphs, such as social network analysis (Qiu et al., 2018) or drug discovery (Gaudelet et al., 2021). The advantage of these approaches is not having to design sets of rules for each individual type of component.

To assemble our dataset, we extracted a graph representation of the TBE system from 15 BIM models in the IFC format. We split the graphs into a training, validation and test set and trained several models with varying amounts of edges being removed from the graph randomly. This setup corresponds to an inductive link prediction setting, in which a model is trained to predict missing links on one set of independent graphs and is later applied to a different set of graphs.

Every node in the graph has positional information in the form of xyz-coordinates, a rotation matrix, the component's bounding box, and the component's IFC class. We use the GCN to embed all nodes in the graph into a latent embedding space, using message passing between connected nodes to aggregate neighborhood information. Then, the embeddings of nodes we want to predict a connection for are concatenated and sent through several layers of a multi-layer perceptron. The result is a probability score that defines the likeliness of an edge existing between the tested nodes. During training, negative edges are sampled to provide the model with sufficient negative examples.

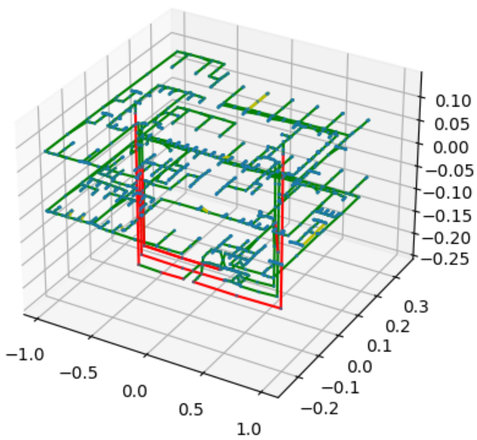

Figure 8. Connections predicted by the neural network model. True positive connections are shown in green, false negatives in red, and false positives in yellow. True negatives are omitted for clarity of the figure.

Our experiments show that the GCN can learn the structure of the TBE system and is able to predict missing links accurately. Figure 8 shows a reconstructed ventilation system as an example. The model manages to predict most connections correctly. Some connections between components that are particularly far apart are not detected. The confusion matrix for the ventilation system can be seen in Table 1.

Table 1. Confusion matrix for the predicted connections shown in Figure 8.

	Predicted Negative	**Predicted Positive**	
Actual Negative	1327	13	1340
Actual Positive	19	1322	1341
	1346	1335	

6. Cloud-based Data Management

An essential element of the energyTWIN toolchain is the content server, which provides a centralized platform for storing, managing, and accessing all project relevant data (Figure 9). The server is designed to store BIM data, which initially is planning data, in the IFC format, point cloud data obtained from field to BIM processes, images (e.g., 360-degree images, RGB and infrared), and sensor data related to TBE. The data is uniquely described and locally identifiable via a link to its RDK from the reference designation system (RDS).

One of the primary advantages of the content server is its ability to integrate (3D) data from different sources via API calls to different services. This ensures that all relevant data is accessible from a single location, making it easier for researchers, engineers, and other stakeholders to collaborate effectively. Furthermore, the server provides an interface for accessing and visualizing data in various formats, such as web frontends and VR or AR applications. This allows stakeholders to view the 3D data in a more immersive and interactive way, enabling them to detect deviations between planning and the built situation more effectively. Differences are documented via a ticketing system connected to the content server.

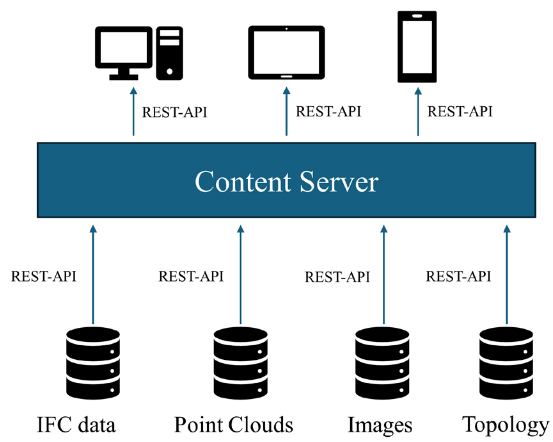

Figure 9. Concept of the cloud infrastructure.

The content server's ability to store point cloud data is of particular importance, as this data type provides a highly accurate representation of the physical environment. By integrating this data into the server, it is possible to create a more comprehensive and detailed model of the building and its surroundings, facilitating better decision-making throughout the construction process.

Overall, the content server provides a valuable resource for the construction industry, enabling better collaboration, data integration, and visualization of 3D data. By providing a centralized platform for storing and accessing construction data, the content server helps to improve the accuracy and efficiency of construction projects while reducing costs and improving safety.

7. AR/VR for Optimized Commissioning

When commissioning the TBE of a given building, it is essential to verify the correct construction of the physical systems, the correct function of said components as well as the correct association between available sensor data and the corresponding TBE elements. Using conventional and available methods, this process is usually both time-consuming and prone to errors, mainly because of the fundamental complexity of modern TBE systems. Errors in this process can cause substantial problems in the building´s management, as the data on which management decisions are made differs from the real-world situation.

AR/VR technology allows for significant improvements in a building's commissioning, for example by overlaying the buildings construction models and sensor data with the actual real-world situation. With the planning model (as-planned) visualized over the actual built situation (as-built), both can be compared to confirm its correct construction or to identify differences. Using the dualistic approach of both AR and VR enables this verification process to be carried out efficiently both on-site and off-site. As the user is free to move around the site in reality or virtuality and is able to view the TBE from a variety of perspectives, construction mistakes or difficulties can be found both fast and accurately. For energyTWIN, Unreal Engine[4] (UE) was chosen as the development framework to realize the AR and VR environments. While UE was primarily known as a framework for developing computer games, recent additions have introduced applications in other fields, such as film and architecture, and with it, interfaces for domain-specific file formats, allowing businesses and industry applications to profit from UE's excellent rendering performance and AR/VR compatibility. For energyTWIN, UE's support for the IFC and point clouds in formats such as e57[5] is essential.

The on-site AR commissioning is solved by overlaying as-planned TBE BIM models over the actual built systems using the MHL2, as shown in Figure 10.

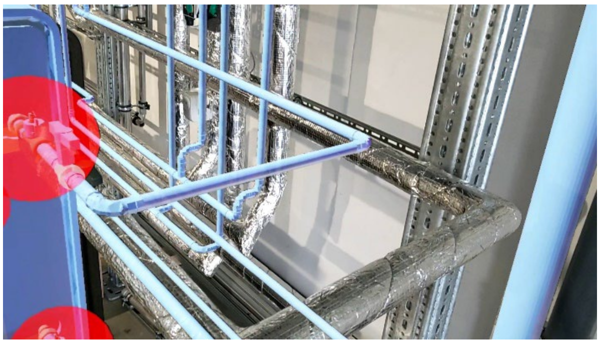

Figure 10. Exemplary visualization of differences between planning and the actual built situation of TBE using AR on-site in Viega Cube Aachen (Viega GmbH & Co. KG).

In order to ensure the correct placement, i.e., georeferencing of the models, a simple registration procedure is performed by the user: First, three points that are easy to spot and reach in the real world are selected in the model. Then, three virtual markers are placed at the corresponding real-world locations. Finally, an algorithm calculates the necessary transformation to move, rotate and scale the BIM model using the corresponding points, so that the virtual elements align with reality. Afterwards, the movement (translation and rotation, also referred to as pose) of the user is tracked by MHL2's inside-out tracking technology.

VR-based off-site commissioning is similar to the AR solution, differing in two aspects: Firstly, the real-world on-site view of the building is replaced by a point cloud representing the inspection environment derived from the MHL2-based capturing system (chapter 2), secondly the use of virtual user locomotion allows an inspection of areas difficult to access during a physical inspection. As 3D scanning becomes increasingly available due to technological advancements and decreasing costs, this approach allows for highly detailed inspections, independent of the user's location. The virtual user locomotion realized using VR controller inputs allows the user to bypass physical restrictions, for example by passing through walls and floors, to discover construction mistakes that could be overlooked or hidden in conventional commissioning processes. Additionally, next to visualizations, in both the AR and VR environment, the correct functionality of the TBE can be verified by displaying operational data received from monitoring sensors: Live sensor data is provided alongside a unique identifier generated by the RDS (Becker et al., 2022) of the associated component over an API and displayed attached to the component, as shown in Figure 11. By providing the operational data for specific components visually, incorrect functionality can be found in a time-efficient manner. This procedure is massively improved in both accuracy and efficiency by the topology API that allows the user to easily isolate a singular system from within the multitude of parallel TBE infrastructure.

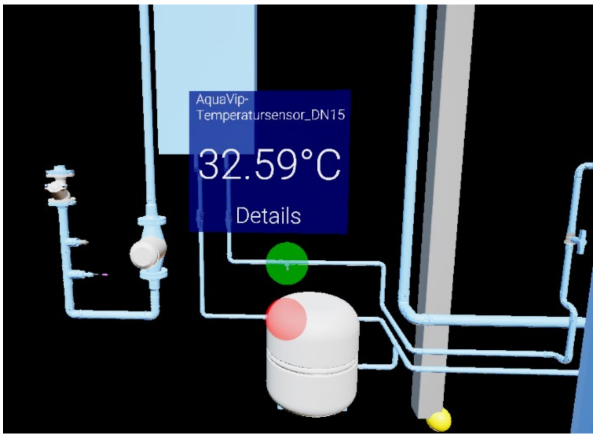

Figure 11. Live data shown for a TBE component of Viega Cube Aachen (Viega GmbH & Co. KG) off-site in VR.

If issues are found, these can be reported directly from within AR and VR using a ticketing system. The ticketing system stores a description of the issue, the identifier of the component that the issue presents itself at and an identifier for the reporting user. The information can be entered by the user using a virtual keyboard. Later, the ticket can be accessed from within AR and VR by a different user who then can be guided to the marked components and presented with the issue information.

4 https://www.unrealengine.com/en-US/
5 https://www.astm.org/e2807-11r19e01.html

According to the user's evaluation, the ticket status can then be updated, allowing for a distinction between urgent and unimportant issues. This system substantially benefits from the dual AR/VR approach, as an issue that is spotted in an off-site inspection can be found during a later on-site inspection, thus allowing the issue to be both presented and solved.

8. Evaluation and Demonstration

In the context of the research project, we utilized two evaluation objects to verify the developed methods. A small-scale demonstrator (Viega Cube Aachen, Viega GmbH & Co. KG) was set up on-site on the RWTH Aachen University campus, including TBE for a warm drinking water system for quick access testing under lab conditions. As large-scale demonstrator, a new office building in Koblenz, Germany (Figure 12) was used to test and demonstrate the energyTWIN toolchain under real-life conditions. Since the building has multiple floors with a large TBE system, we focussed on the 6th floor and its technical room. Here, our focus lies on heating, cooling, and water systems. These are advantageous, because we can for example perform as-planned/as-built comparisons with the system elements, obtain and visualize thermal data, and derive topology and sensor data.

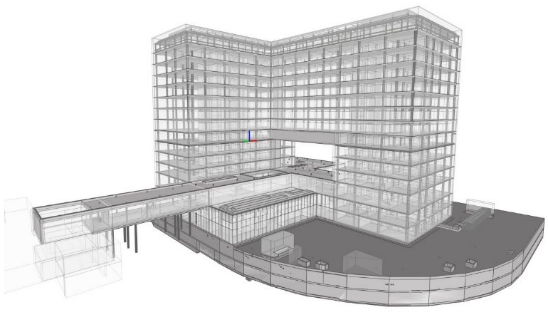

Figure 12. BIM model of the large-scale demonstrator in Koblenz, Germany (data source: Aachener Grundvermögen Kapitalverwaltungsgesellschaft mbH).

Among other aspects, we evaluated the developed capturing system. Before starting the capturing process, a calibration, as described in section 2, was done. This allowed us to evaluate the basic functionality of calibration, the capturing process with the sensors, and the subsequent methodology for parallel generation of RGB and thermal point clouds. The resulting point clouds had accuracies between 1 and 3 cm. Sufficient detail can be seen in both, the RGB colored point cloud and the thermal point cloud. The evaluation of AR and VR showed that the point clouds and BIM models are best visualized room-wise, to keep the data at a processable amount. For example, the number of individual BIM objects in one scene should be kept below 1.000, specifically for the mobile hardware of the MHL2. This ensures that the data can be rendered at a high frame rate in real-time, significantly improving the user experience. To accomplish this, we additionally manually optimized the BIM models, by merging separate pieces of objects together, leading to a significant reduction in the number of individual objects and improved rendering performance. For AR, the combination of MHL2's pose tracking system and the corresponding point-based registration method provided very good results, enabling an augmented view of reality with the BIM planning model overlaying the built TBE and allowing users to freely move around to easily spot differences.

9. Conclusions and Outlook

In this paper, we presented the realized toolchain for automatically creating a digital twin of TBE based on planning models and for enhancing TBE commissioning with BIM-enabled methods realized in the project energyTWIN. Using various technologies and tools from different areas of the digital transformation, such as data capturing tools, cloud-based data serving architectures, BIM, AI, AR and VR, we are able to enhance the process of digital twin creation and TBE commissioning by updating the as-planned BIM model to an as-built model ready for the operational phase. We believe that the current state of the used technology implementations can already provide a substantial benefit and paves the way for maximizing energy efficiency and savings. It is precisely the combination of all these technologies in one toolchain that enables a maximum of improvements.

In future developments, specifically the as-planned/as-built comparison methods could be further enhanced, for instance by combining them to overcome their individual strengths and weaknesses. Furthermore, the methods could be adapted for mobile computing for them to run in real-time on mobile devices, enabling real-time on-site analyses. For this, the presented capturing, management, and comparison processes would need to be combined efficiently. Furthermore, the digital twin could be implemented in the operational phase and methods for optimizing operational processes could be developed, for example using large language models for better information communication between the digital twin and humans.

Acknowledgements

The authors gratefully acknowledge the financial support of the German Federal Ministry for Economic Affairs and Climate Action in the project "EnOB:EnergyTWIN - Energiediagnose-stecker Digitaler Zwilling. Neue sensorgestützte und KI-basierte Methoden für die digitale, BIM-basierte Inbetriebnahme von technischen Anlagen in Hochbauwerken und deren energetische Systemoptimierung" (reference number 03EN1026). Furthermore, we would like to express our sincere gratitude to Viega GmbH & Co. KG for providing access to the Viega Cube Aachen.

References

Arayici, Y., Onyenobi, T., & Egbu, C. (2012). Building information modelling (BIM) for facilities management (FM): The MediaCity case study approach. International Journal of 3-D Information Modeling (IJ3DIM), 1(1), 55-73.

Bazjanac, V. & Kiviniemi, A. (2007) "Reduction, simplification, translation and interpretation in the exchange of model data," Proceedings of the 24th Conference on Bringing ITC Knowledge to Work, 78(Gsa 2003), pp. 163–168.

Becker, R., Blut, C., Emunds, C., Frisch, J., Heidermann, D., Kinnen, T., Lenz, A., Möller, M., Pauen, N., Rettig, T., Schlütter, D., Wenthe, M., Blankenbach, J., Bleimann-Gather, G., Fütterer, J., Jungedeitering, J. & van Treeck, C. (2022). energyTWIN – BIM-assisted, automated processes for commissioning in building services engineering. Proceedings of the 39th Symposium on Automation and Robotics in Construction (ISARC 2022), Bogotá, Colombia, pp. 558 – 565

Bosché, F., Ahmed, M., Turkan, Y., Haas, C. T., & Haas, R. (2015). The value of integrating Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The case of cylindrical MEP components. Automation in Construction, 49, 201-213.

Chan, K.L. & Qin K. (2017). Biomass burning related pollution and their contributions to the local air quality in Hong Kong. Int. Arch. Photogramm. Remote Sens. Spatial Inf. Sci., XLII-2/W7, 29-36. doi.org/10.5194/isprs-archives-XLII-2-W7-29-2017.

Chen, J., & Cho, Y. K. (2018). Point-to-point comparison method for automated scan-vs-bim deviation detection. In Proceedings of the 17th International Conference on Computing in Civil and Building Engineering, Tampere, Finland (pp. 4-7).

Chevallier, Z., Finance, B., & Boulakia, B. C. (2020). A Reference Architecture for Smart Building Digital Twin. In SeDiT@ ESWC (pp. 1-12).

El Jazzar, M., Piskernik, M., & Nassereddine, H. (2020). Digital twin in construction: An empirical analysis. In EG-ICE 2020 Workshop on Intelligent Computing in Engineering, Proceedings (pp. 501-510).

Ellmauthaler, A., da Silva, E. A., Pagliari, C. L., Gois, J. N., & Neves, S. R. (2013). A novel iterative calibration approach for thermal infrared cameras. In 2013 IEEE International Conference on Image Processing (pp. 2182-2186). IEEE.

Gaudelet, T., Day, B., Jamasb, A. R., Soman, J., Regep, C., Liu, G., ... & Taylor-King, J. P. (2021). Utilizing graph machine learning within drug discovery and development. Briefings in bioinformatics, 22(6), bbab159.

Gumhold, S., Wang, X., & MacLeod, R. S. (2001). Feature Extraction From Point Clouds. In IMR (pp. 293-305).

Graham, B. & van der Maaten, L. (2017) "Submanifold Sparse Convolutional Networks." Available at: https://arxiv.org/abs/1706.01307v1.

Khajavi, S.H., Motlagh, N.H., Jaribion, A., Werner, L.C. & Holmstrom, J. (2019). Digital Twin: Vision, Benefits, Boundaries, and Creation for Buildings. IEEE Access 7, 147406–147419. https://doi.org/10.1109/ACCESS.2019.2946515

Kinnen, T., Blut, C., Effkemann, C., & Blankenbach, J. (2023). Thermal reality capturing with the Microsoft HoloLens 2 for energy system analysis. Energy and Buildings, 113020.

Kipf, T. N. & Welling, M. (2016) "Semi-Supervised Classification with Graph Convolutional Networks," 5th International Conference on Learning Representations, ICLR 2017 - Conference Track Proceedings.

Lagüela, S., González-Jorge, H., Armesto, J., & Herráez, J. (2011). High performance grid for the metric calibration of thermographic cameras. Measurement Science and Technology, 23(1), 015402.

Lee, J., Son, H., Kim, C., & Kim, C. (2013). Skeleton-based 3D reconstruction of as-built pipelines from laser-scan data. Automation in construction, 35, 199-207.

Lu Q., Xie X., Heaton J., Parlikad A.K., Schooling J. (2020) From BIM Towards Digital Twin: Strategy and Future Development for Smart Asset Management. In: Borangiu T., Trentesaux D., Leitão P., Giret Boggino A., Botti V. (eds) Service Oriented, Holonic and Multi-agent Manufacturing Systems for Industry of the Future. SOHOMA 2019. Studies in Computational Intelligence, vol 853. Springer, Cham.

Muehlich, M., & Aach, T. (2007). High accuracy feature detection for camera calibration: A multi-steerable approach. In Pattern Recognition: 29th DAGM Symposium, Heidelberg, Germany, September 12-14, 2007. Proceedings 29 (pp. 284-293). Springer Berlin Heidelberg.

Pauen, N. P. M. (2022). Graphbasierte Algorithmen und gesamtheitliche Repräsentation von Systemen der TGA mit BIM und Linked Data. Dissertation, Rheinisch-Westfälische Technische Hochschule Aachen

Pauen N., Schlütter D., Frisch J., van Treeck C., (2021). TUBES system ontology: Digitalization of building service systems. Proceedings of the 9th Linked Data in Architecture and Construction Workshop, Luxembourg, pp. 43-54.

Placht, S., Fürsattel, P., Mengue, E. A., Hofmann, H., Schaller, C., Balda, M., & Angelopoulou, E. (2014). Rochade: Robust checkerboard advanced detection for camera calibration. In Computer Vision–ECCV 2014: 13th European Conference, Zurich, Switzerland, September 6-12, 2014, Proceedings, Part IV 13 (pp. 766-779). Springer International Publishing.

Qiu, J., Tang, J., Ma, H., Dong, Y., Wang, K., & Tang, J. (2018, July). Deepinf: Social influence prediction with deep learning. In Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining (pp. 2110-2119).

Schlichtkrull, M., Kipf, T. N., Bloem, P., Van Den Berg, R., Titov, I., & Welling, M. (2018). Modeling relational data with graph convolutional networks. In The Semantic Web: 15th International Conference, ESWC 2018, Heraklion, Crete, Greece, June 3–7, 2018, Proceedings 15 (pp. 593-607). Springer International Publishing.

Sepasgozar, S. M., Hui, F. K. P., Shirowzhan, S., Foroozanfar, M., Yang, L., & Aye, L. (2020). Lean practices using building information modeling (Bim) and digital twinning for sustainable construction. Sustainability, 13(1), 161.

Volk, R., Stengel, J., Schultmann, F. (2014). Building Information Modeling (BIM) for existing buildings Literature review and future needs. Autom. Constr. 38, 109–127. https://doi.org/10.1016/j.autcon.2013.10.023