BIM-assisted, automated processes for commissioning in building services engineering

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Abstract –

State-of-the-art building energy systems exhibit a high technical complexity. In the commissioning phase, technical building elements (TBE) are put into operation trade-by-trade and as linked complete systems. Besides the correct wiring on component level, instantiating the building automation and detecting errors is a cumbersome process in practice. The paper addresses a novel interconnected toolchain to support commissioning energy systems through digital processes in combination with energy system related digital BIM twins– the "energyTWIN". This energyTWIN digitizes and automates the process chain in the commissioning of TBE and building automation with its highly complex interrelationships in constant exchange between reality and the BIM model (digital twin) as completely as possible.

By increasing energy efficiency with the novel processes of energyTWIN, a contribution to the worldwide goal of reducing energy consumption can be achieved.

Keywords –

Building Information Modeling; Technical building equipment; Data capturing; Indoor positioning; Virtual and Augmented Reality

1 Introduction

Nowadays, TBE are highly complex and interconnected systems. After dimensioning the hydraulic system and planning as Piping and Instrumentation Diagram (P&ID), TBE are today planned as 3D model with semantic (manufacturer) data using Building Information Modeling (BIM). In practice, building automation with its functional descriptions is handled separately. Both domains are typically not linked and uniform data labels of TBE are defined often separately without using the (naturally existing) classification system of BIM. So, the TBE functions correctly and according to its control strategy during the operational phase, the commissioning must correspond to the planned configuration, or, the TBE control system must be customized to the actual built situation. Therefore, in the energyTWIN project, modern methods for high-resolution as-built data capturing (reality capturing) are being developed and refined with the aid of Artificial Intelligence (AI)-based data filtering and feature extraction for the automated recognition and classification of components and their topological, functional and informational interrelationships.

Crucial for automated workflows are uniform, generic (manufacturer-neutral) Reference Designation Systems (RDS) for the identification of TBE components (section 2). For data capturing of the actual installed TBE, efficient methods based on photogrammetry, laser scanning, infrared measurement technology, etc. will be developed and refined as described in section 3. This also includes methods for indoor positioning (pose tracking) and georeferencing of the captured data. Georeferencing is needed for comparisons to the as-planned BIM model and will be used in Virtual and Augmented Reality (VR/AR) applications of section 4. A comparison between the planned and the actual as-built situation will be realized using AI-based methods for automated recognition and classification of components and their topological relationships (section 5). A cloud-based system will connect all acquired relevant data on field level. Fault detection and diagnosis increases system and supply reliability (section 6). Finally, all developments will be prototyped and evaluated (section 7). Several, partly AI-supported methods will be fused to derive a

BIM model that reflects the actual situation (as-built) for planning and operational processes including aspects of time and costs (5D BIM in the phase of building life cycle following the commissioning of the TBE).

The energyTWIN, for the first time, employs AI-based approaches to combine image- and laser-based geometric and semantic data of building and system components with simultaneously captured data on field level. Furthermore, the modern technologies VR/AR are used for georeferenced and interactive visualizations as well as updating the BIM-based digital twins of the TBE. Finally, the RDS ensures the unique identification of objects during the various processes and data exchanges.

2 Reference Designation Systems

RDS are used for the unique identification of objects at different levels of granularity. Identifiers can be implemented as Global Unique Identifier (GUID) by a combination of alphanumeric characters or by a hierarchical structuring of data according to certain aspects such as location-, function- and signal related structure. GUIDs are used by BIM software applications and in the Industry Foundation Classes (IFC) data model [1]. The IFC schema is a standardized data model that defines the identity, semantics, characteristics, attributes, and relationships of objects, abstract concepts, processes, and people in a logical form. RDS with a hierarchical structuring of data are used by humans to reference objects across different models and documents. The structuring and level of detail of these systems depends on project-specific conditions as well as use cases and can therefore not be defined globally [2]. However, the reference designation should be as short as possible and as detailed as necessary. Aspects such as readability, memorability and uniformity of the reference designation system must be considered.

RDS map a "component-of" structure via hierarchical structuring according to various aspects. Frequently, a distinction is made between location, functional, and product-related aspects [3]. The location-related aspect describes the installation site or the installation location of an object. Entities of the local structure can be, among others, site, building, storey, area, room, or segment as well as outdoor areas. The product-related aspect defines the composition of the object. It shows the division of an object into individual parts. Entities of the product-related structure are defined, among others, in standardized classification schemes such as Table 02 of DIN EN IEC 81346 - 2 [4] or Table 03 of VDI 3814 - 4.1 [5]. The functional-related aspect describes the respective function or task of a system and subdivides it hierarchically. Entities of the function-related structure are, among others, functional systems, technical systems, and components. These aspects can be used isolated from each other or interrelated to reference objects. Independently of this, the marking in the individual levels of the aspects takes place via a defined sequence of alphanumeric characters [3].

As part of a literature review, 50 RDS were considered, originating from the private (building automation, utilities), public (cities, state offices, federal offices) and scientific (universities, university hospitals) sectors. In addition, common standards were considered. Especially the reference designation systems of DIN EN IEC 81346 [2], VDI 3814 [5] and the Buildings Unified Data Point naming schema for Operation Management (BUDO) [6] were evaluated positively. Based on these findings and aligned with the concepts of DIN EN IEC 81346, a possible structure for a reference designation system is shown in Figure 1.

To implement a RDS into the planning process, the systems must be streamlined with existing digital data models. The digital model, also known as the BIM model, is the central instrument and is considered the "single source of truth". One option for structuring and exchanging the information is the open IFC standard. Depending on the aspect under consideration, structures for mapping these already exist in the IFC data model. There are five classes (*IfcSite, IfcBuilding, IfcBuilding Storey, IfcRoom* and *IfcZone*) describing the location-related aspect, one class with multiple types (*IfcSystem*) to describe the function-related aspect as well as multiple classes and subtypes to describe the product-related aspect. For the description of the signal-related aspects, no classes are currently available in IFC. Therefore, the structures can only be considered as attributes on elements. To map these, the IFC data model would have to be extended to include classes such as *IfcSignal* and the relationship *IfcRelConnectsSignalToElement*.

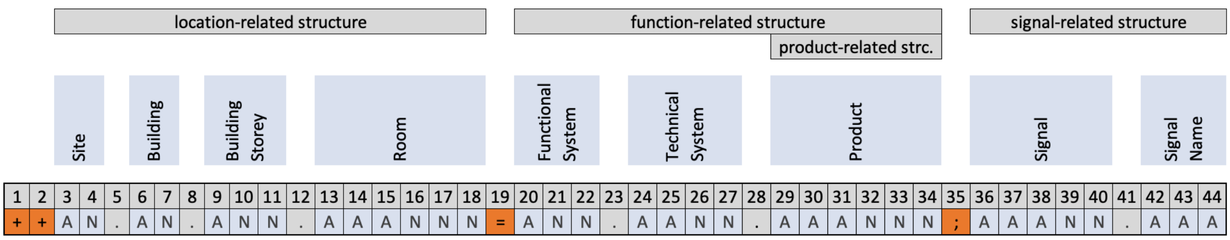

Figure 1: Possible structure of the RDS (A = alphabetic character, N = numeric character)

Corresponding types of *IfcSignal* could be based on existing classifications in the BUDO schema.

3 Efficient methods for reality capturing

For digitizing and automating the process chain during the commissioning of TBE, capturing geometric and semantic data of the realised state is essential. This requires a suitable capturing system, favourably with various sensors and interfaces. State-of-the-art is to use laser scanning and photogrammetry [7]. Often laser scanners are coupled with cameras to create coloured point clouds that represent the environment very realistically. Roughly, laser scanning can be categorized into two types: Terrestrial Laser Scanning (TLS) and Mobile Laser Scanning (MLS). While in TLS the resulting points clouds typically have a higher accuracy in comparison to MLS, MLS is more flexible and time efficient. In the field of photogrammetry, combining images taken from different points of view into a common coordinate system by determining the mutual orientation by means of bundle block adjustment over identical (homologous) points, has long been the standard method [8].

In the energyTWIN project, the goal is to create a flexible and easy to use system that is able to capture geometry, visual information, and additional properties of TBE, such as thermal data. The geometry contains information about size and shape of an object, an image contains information such as colour, and thermal data insight into the functionality of an object. A fusion of multiple data promises an improved and holistic classification of objects, since each part of information provides further indications about an object and reduces the number of object possibilities.

A potentially easier to use and more flexible solution than a stationary TLS or a conventional MLS, is the Microsoft HoloLens 2 (MHL2). The MHL2 is a mobile mixed reality (MR) head-mounted system. Its built-in sensors already include a depth and a colour (RGB) camera to create coloured point clouds. Since the MHL2 is head-worn, it has the same advantages as MLS in terms of flexibility and capturing speeds, compared to TLS. Furthermore, with its fully-fledged MR capabilities, it is a combined data capturing and MR system and enables us to realize the project goals described in section 3 and 4. In a detailed evaluation we found that the MHL2 achieves a sufficient accuracy of 2-5 cm, which is suitable for the project goals. Additionally, we are extending the system with external sensors, such as a thermal camera. We attached a FLIR ADK thermal camera directly to the MHL2 with a 3D-printed mount (Figure 2) and calibrated the system. To incorporate the thermal data into point clouds, we developed a mapping method, which enables generating point clouds coloured with RGB and thermal camera data.

A prerequisite for fusing data of different sensors is that the data must be transformed into a uniform coordinate system (co-registration). For example, separate point clouds must be registered to each other or thermal images must be projected onto the point clouds.

Figure 2. System setup consisting of the MHL2 in combination with the FLIR ADK thermal camera

The registration of point clouds can be achieved using methods such as RANSAC [9] or Iterative Closest Point (ICP) [10]. These techniques are also used for MLS to register point clouds in real-time. For example, using visual odometry [11] or plane-based methods as shown by Wujanz et al. [12]. Another example of fusing image data and other sensor data is shown in Effkemann et al. [13]. Furthermore, many manufacturers already offer software for the registration process, for example Riegl RiSCAN PRO. Initial methods and results to register thermal images with a model of the outer shell of a building via homogeneous points and project the images onto the facades are shown by [14]. Many methods, however, require lengthy manual steps by the user. Next to constructing a reality capturing system, an important goal of the energyTWIN project therefore is the development of an automated registration process.

Key-information for registering point clouds, georeferencing data or also for visualizing data in VR and AR, are the viewing direction (orientation) and location (position), referred to as pose, of the user or more specifically the device. Any movement of the user must be tracked in real-time, so the pose stays up to date. This is referred pose tracking. There are two basic types of pose tracking: outside-in and inside-out. In outside-in pose tracking, an exterior device, for example attached to a wall, observes the device carried by the user to estimate its pose. In inside-out pose tracking, the tracking device is carried by the user and it observes its surroundings for pose estimation. Outdoors, typically, outside-in methods, e.g. satellite-based localization systems (GNSS), are used. Since GNSS are usually not applicable in covered areas, methods based on the radio technologies Ultra-Wideband (UWB), Bluetooth or WLAN, as well as on infrared or ultrasound, are required for indoor applications [15].

However, these systems need a complex installation. Therefore, the project focuses on inside-out methods, specifically camera-based or laser-based methods, to offer flexibility. In contrast to outside-in, inside-out methods do not require external infrastructure.

A pose requires a reference system, local or global. In VR, typically a local coordinate system is used for the virtual world, oriented during the setup process of the VR equipment. For example, the front facing direction is set, so that the user always starts relative to it. In AR, also often local coordinate systems are used, for instance initialized when the AR system is started. Objects then appear relative to the starting pose of the user. Since AR is much more linked to the physical world than VR, it is beneficial to apply a global coordinate system like World Geodetic System 1984 (WGS 84) or another existing real-world coordinate system, such as a building coordinate system. A common virtual and physical coordinate system, such as a building coordinate system, enables attaching virtual information to physical elements or augmenting these as shown in [16, 17].

Therefore, we will realize a method to transform the MHL2 from its local coordinate system into a building coordinate system and a method to accurately track the pose of the MHL2 in the building coordinate system. For this, we will use the georeferenced BIM-based 3D planning model to register the MHL2 to the building. Building parts of the virtual model can be used as a reference to find the pose of the user in the physical building and then calculate the transformation from the local to the building coordinate system. Afterwards, we will track the user's pose relative to the initialization pose in the building coordinate system. A promising method for this is Simultaneous Localization and Mapping (SLAM) [18]. SLAM uses pose information to generate a local map (3D point cloud) of the environment. The map in turn is employed for pose estimation. Using bundle block adjustment, the relative camera poses are optimized based on the 3D point cloud to obtain a highly accurate local trajectory. For a globally consistent trajectory, a loop closure method is applied. Loop closure refers to returning to a previously visited location and incorporating past pose information into current estimates. The most common types of SLAM are camera-based visual SLAM (V-SLAM) and laser-based light detection and ranging (LiDAR)-SLAM. While V-SLAM uses corresponding salient points in sequences of photographs (feature points) to estimate the motion of the physical camera, LiDAR-SLAM uses sequences of 3D point clouds. While V-SLAM has more information available than LiDAR-SLAM due to the use of cameras, it is more susceptible to different lighting conditions. This must be taken into account, especially for indoor pose tracking in dark rooms.

4 VR/AR for semantic data enrichment

In the energyTWIN project, VR and AR are utilized to visualize a variety of data, to support the user in visually comparing the planned (as-planned/as-designed) and the real-world (as-built) situation, in order to correct the as-planned model with the detected deviations.

VR and AR systems differ by the amount of digital and real-world content the user is presented with. In VR systems, the user can only see digital content and his real-world location becomes less relevant. In room-scale VR, as often possible with modern VR systems, the user is able to move around in a virtual environment and interact with it by moving in his physical environment with hand-held controllers or other devices. In an AR system, a large part of the visual input consists of the real world which the user is surrounded by. The project goal is to develop a system, which allows the user to walk through the building to commission the different parts of the TBE. Therefore, a stationary AR system is not suitable, but a mobile one including georeferencing is needed. For a mobile georeferenced AR system, three subtasks need to be solved: (1) the data needs to be prepared and visualized in real-time, (2) the physical world needs to be observable and (3) methods need to be implemented to combine both worlds.

For energyTWIN, a two-pronged approach has been chosen. In a VR system, the user will be able to interact off-site with purely digital content and use combinations of data from the as-planned model and the captured point cloud data, which represents the as-built situation. In AR, the user will be able to overlay selected data in the real-world on-site and interact with it, for example, the as-planned model, to visually compare it to the actual built situation. As a development framework, we are using Unreal Engine (UE). While UE primarily is a framework for developing computer games, recent additions like interfaces for IFC and point clouds enable the software for business and industry applications. In our VR solution, the user will have two basic datasets available that form the digital world surrounding him: On the one side, the as-planned BIM model in the form of geometry components from IFC and on the other side, point clouds that represent the real-world situation. The user will be able to move around by physically moving and by so called teleporting. For teleportation, the user aims the controller at a point in the virtual space and by pressing a button, he is virtually transported to this location. IFC elements offer much more information than only the geometry. The user will be able to access this information via a User Interface (UI) directly in VR (Figure 3).

The UI consists of a virtual panel attached to the left and a laser pointer to the right virtual hand. The developed RDS (section 1) is used to filter by criteria such as function type of the system.

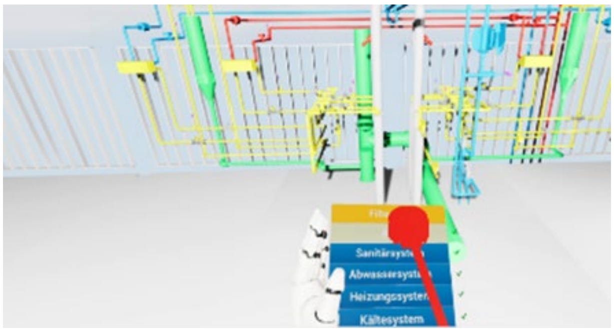

Figure 3. UI in VR

When a deviation between the as-planned and as-built situation is identified, the user can place an issue, using a ticket system. Selected from a predefined list, comments can be attached to individual components of the IFC model. The issues will be exportable using the IFC-based standardized BIM Collaboration Format (BCF), to allow interoperability between the subsystems of energyTWIN.

In the AR, the user will be able to visualize the planned model (IFC model) on-site and interact with it with the MHL2 and its gesture recognition system (Figure 4). For possible performance issues with the MHL2, a solution involving pixel streaming technologies is being tested. With it, heavy processing tasks are outsourced to an external computer or cluster and only the prerendered images are sent to the MHL2 to be displayed. With this AR system, the user will be able to capture data only visible on site and will be guided through processes such as TBE installation or maintenance.

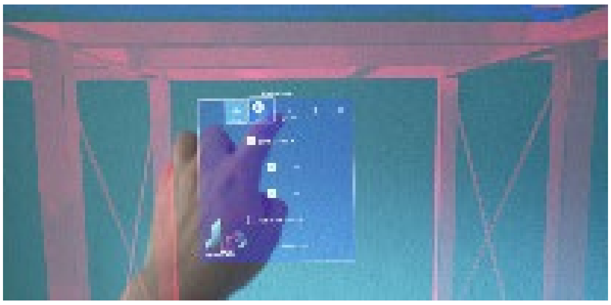

Figure 4. User interaction in AR

5 AI based methods for element recognition and classification

In the first step, we focus on developing methods for the automatic filtering and extraction of features to recognize and classify TBE and its topological, functional and informational relationships from image-, laser- and infrared-based data, to obtain the as-built BIM. In a second step, the extracted TBE should be automatically compared with the as-planned BIM in order to model the objects geometrically and semantically. In addition, rule-based methods of clash detection are also integrated within this operation to detect differences between the models. This process allows the as-planned BIM to be upgraded to an as-built BIM. A challenge is handling the large data amounts and their complexity, since these are hardly manageable manually, so that automated methods are indispensable. Therefore, we are investigating which approach suits the project´s purposes best.

Today, AI enables analysing large and possibly unstructured data sets (big data). Two possible options are classical Machine Learning (ML) methods or more recently Deep Learning (DL) using artificial neural networks (ANN). AI-based methods have already been successfully applied to building element reconstruction, for example of indoor scenes [19]. In this context, the neural networks PointNet [20] and VoxelNet [21] are particularly noteworthy, which differ in the way geometric features are processed and classified. However, modified and refined models such as Voxel-FPN [22] have also proven to be effective in detecting objects in outdoor and indoor environments. Some models such as the MVX-Net [23] also fall back on data from different sensors and merge the separate classification results to achieve a higher level of accuracy. Another possibility for system topology recognition is the classification of building technology time series, as described in their basic functioning in [24]. While DL can handle large amounts of data, its disadvantage is that it also requires large amounts of training data and significant training time. Furthermore, numerous aspects such as the selection of suitable parameters and training features must be considered for preventing problems such as overfitting of the models.

To support the AI, we will integrate the as-planned BIM into the process. This will allow us to apply existing information to the algorithms (knowledge-based). Next to the knowledge-based solution, we will also realize a geometry-based method without prior knowledge, to analyse the data based on geometrical properties. As a third option, we will implement a DL-based solution. Finally, all solutions will be compared, and the most suitable solution for the task will be identified.

The knowledge-based approach is characterized by the fact that the as-planned BIM acts as a reference in the analysis of the captured point cloud data. A prerequisite is a point cloud sampled from the as-planned BIM [25]. To generate such an as-planned point cloud, a ray-casting algorithm will be utilized. Furthermore, the captured point cloud will be segmented object-wise by deriving a bounding box from the corresponding objects from the as-planned BIM and transferring it to the as-built point cloud to cut out an object-specific point cloud. Therefore, a registration of the as-planned BIM and the captured point cloud must be realized first, so that both are in a common spatial coordinate system. Following this process, certain object data can be transferred directly from the as-planned to the as-built BIM model. To investigate the relative position of the objects, an approach of a two-stage co-registration with coarse and fine positioning will be investigated using known techniques of geometric hashing [26], RANSAC [27] and (modified) iterative closest point (ICP) algorithms [28-30]. On the other hand, the method presented in [31] for the as-built modelling of cylindrical objects using a Hough Transformation will be investigated on its application potential for the described project goal.

For the geometry-based approaches, the detection of corners and edges via the investigation of local point densities and neighbourhood relationships [32] or the skeletonization of object representations in the as-built point cloud [33] will be analysed.

In terms of a DL-based approach, existing methods for point cloud semantic and instance segmentation [34-36] will be evaluated, further customized and advanced to better deal with the particular challenges of TBE.

6 Cloud-based system for data provision and failure diagnostics

The central element of the energyTWIN system architecture is the content server, which stores the BIM model, initially in the planning state, in the form of geometric IFC data of the building and its TBE (Figure 5). Each object of the TBE is uniquely described and locally identifiable via a link to its id in the RDS (see section 2).

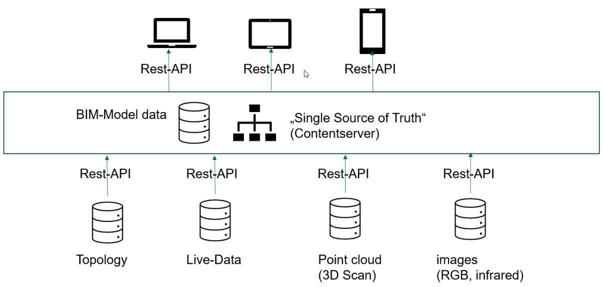

Figure 5. Concept of the cloud infrastructure

The data provided by the project partners, such as topological data, point clouds from laser scanning systems, camera images in the RGB and infrared range, as well as continuous operating data from the field, are not directly stored on the content server, but are held in separate cloud-based systems, each with their own query interfaces. The content server queries these data sources as needed and makes the results available to the user in real time in the context of the BIM model and its RDS. For this purpose, the content server in turn provides an interface, so that clients, such as web-interfaces or smartphone apps, can be connected and all collected data is visualized, easily comparable and always available.

In this way, the commissioning of the TBE is optimized. Deviations from the planning status, which result from the evaluation of scan and photo data, are documented via a ticket system connected to the content server, with the aim of correcting the as-planned model and, thus, creating a valid modified BIM model that corresponds to the actual conditions.

In the finished model, the sensors located in the field, such as temperature or pressure sensors, are then displayed at the topologically correct location throughout the entire operating time of the building, and the operating data provided by the sensors can be easily queried at any time, which greatly facilitates both fault diagnostics and maintenance. Should maintenance and other tasks become necessary in the future, planning and preparations can be made by combining scans, 3D views and continuous field data with the digital twin, to significantly reduce the number of necessary on-site visits.

7 Evaluation and Demonstration

All the developed methods and the results are evaluated throughout this project. For this purpose, various demonstrators are being set up for testing the relevance of the developed methods in practice. A small-scale demonstrator (Figure 6) was set up on-site, including several technical installations for a drinking water system.

Figure 6. Point cloud (NavVis VLX) of the ViegaCUBE (Viega GmbH & Co. KG)

This is used for all the partners to exploit synergies and to test the already linked work progress. The demonstrator was already put into operation and a first digital twin of it was created. To create the twin, the NavVis mobile mapping system VLX and the terrestrial laser scanner Riegl VZ400 were used as reference systems, next to the MHL2. First evaluations show that an accuracy of 1-3 cm can be expected from the MHL2, therefore, on a level with dedicated MLS systems. Further, more detailed evaluations will follow later in the project. On the one hand, the digital twin is represented through a point cloud. On the other, the NavVis software offers a web-based viewer, with built-in panorama, point cloud views, and the possibility of creating points of interest. It is used by the project partners to collaborate on the digital twin.

After testing the developed processes on a small-scaled system and evaluating the techniques and methods, they will be evaluated based on their applicability and relevance and subsequently changed or improved. The next step is the preparation of a large-scale demonstrator for further testing and evaluating. Therefore, the associated project partner provides a new constructed office building in Koblenz, Germany. The evaluated methods in the demonstrators provide insights into the accuracy of the applied methodology of the overall project and can, when considered, improve the overall accuracy.

8 Conclusions and Outlook

Within this paper we presented first results of our research. Technologies like indoor positioning, VR/AR, and various sensors (laser scanning, infrared etc.) and mobile devices (MHL2) are combined for data capturing. AI based methods will be used for object element classification and comparison to the as-planned model as well as for detecting and analyzing topological and functional relationships in TBE. A cloud-based system provides and exchanges the data on-site. RDS are used for unique building and TBE element identification. Only the combination of all these technologies enables enough knowledge about deviations between the BIM-planned TBE and its actual commissioning, so that the as-planned BIM model can be updated to the actual, built situation, and subsequently used for optimization of TBE. This promises an improved commissioning for increasing energy efficiency in the building's operation phase.

Future research will focus on increasing the accuracy of the capturing system which also involves increasing the pose tracking accuracy. Further improvements will involve increasing the automation level, for example, the AI-based segmentation and classification of TBE, also for complex elements.

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