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Closed-Loop Engineering Approach for Data-Driven Product Planning

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Abstract

This contribution introduces an approach for data-driven optimization of products and their product generations through a Closed-Loop Engineering approach resulting from the German research project DizRuPt. The approach focuses on data-driven product planning by ensuring data consistency and traceability between product planning, product development, and product operation by combining aspects and functions from Product Lifecycle Management (PLM) and the Internet of Things (IoT). The presented approach is illustrated and validated by pilot applications from the research project.

Keywords: closed-loop engineering, product lifecycle management (PLM), internet of things (IoT), data-driven design, product optimisation

1. Introduction

Increasing international competition is putting many companies under pressure. At the same time, global megatrends such as digitization create countless new opportunities and risks for the manufacturing sector. With the Industry 4.0 paradigm, a fundamental change in value creation is emerging for manufacturing companies. By combining local information processing and global communication capabilities in tomorrow's products and production systems, new kinds of systems are emerging (so-called cyber-physical systems (CPS) (Broy, 2010; acatech, 2011)), which are increasingly being offered to customers in the mechanical and plant engineering sector. Distributed systems and the use of industrial data analysis processes tailored to them open up fascinating perspectives, not only for the products themselves but also for their further strategic development. Already today, systems in the field generate a large amount of operational data (machine and process data), which has so far primarily been used for additional customer functions (e.g., predictive maintenance) (Reichel et al., 2018; Dienst, 2014). However, with the advent of CPS, data increased significantly. The data are available to additional stakeholders in the value-creation network through the networking of CPS via the internet. Thus, machine manufacturers' targeted and systematic analysis of usage data provides significant impetus to improve their products. According to (Lueth et al., 2016; VDMA, 2016), this is one of the most important fields of application for industrial data analytics. (HNI, 2018)

The challenge, however, is to identify, collect and evaluate the correct data and make it usable for the further development of the company's products. Establishing such an approach in manufacturing companies requires significant technology, organization, and people changes. Firstly, there is a lack of suitable methods and procedures for data-driven product planning and design. Secondly, the implementation of such an approach requires a socio-technical consideration. In addition to integrating sensor technology into the products and using suitable data analysis procedures (technology), the effects on the organization and the people must also be clarified. Corresponding processes must be defined, the impact on the organizational structure must be analyzed (organization), and the data-based approach requires new competencies in the development organization (people). Third, the planning of complex technical systems is based primarily on IT tools. While data of the operation phase is collected and processed in so-called Internet-of-Things systems (IoT), targeted feedback and processing into the planning and design phase and the Product Lifecycle Management system (PLM) used there have only taken place in the rudimentary form (Dienst, 2014). Alternatively, they are only conceptually described and prototypically applied in academic research (Kiritsis, 2011; Dickopf et al., 2019; Dickopf, 2020; Dickopf, 2021). The coupling of machine-related IoT platforms and PLM systems is thus another challenge that must be solved both technically and, above all, methodically.

The German research project DizRuPt deals precisely with these challenges and forms the basis for this contribution. The project pursues the development of a framework to enable companies to utilize usage data of their products independently and in a targeted manner in product planning. Therefore, methods and tools will be provided to support the product investigation, data analysis, product redesign, and improvement and be merged in a reference process. In addition, a second concept describes how data consistency and provisioning can be ensured between the leading data management systems to generate added value from the data of the other prevailing system for both the operation phase (IoT system) and the planning and development phase (PLM system). (HNI, 2018). Five fields of action (AF), shown in Figure 1., are addressed by the project. Previous publications have concentrated in particular on methods for product investigation (Meyer et al., 2020a), data analytic (Massmann et al., 2020), and strategic product planning (Meyer et al., 2020b), and focusing in particular on the aspects of organization and people. This contribution deals with the concepts of technical support for data networking and provision, which be assigned to the fifth field of action, "tool support."

The results of this contribution are developed according to the CASE research cycle (clarification – analysis – synthesis – evaluation) after Müller (2013). This section formulates the problem statement and clarifies the underlying research and contribution objective. Section two provides insight into the analysis phase results by giving a short overview of the most relevant terms in the corresponding fields. In section three, the synthesis stage, a Closed-Loop Engineering concept is presented to reach the target objective, which, on the one hand, explains the essential steps for enabling companies to perform data-driven product planning. On the other hand, it contains the necessary concepts and specialist objects for end-to-end data networking between PLM and IoT systems. In section four, the concept evaluation is based on one of the pilot applications in the research project by providing an excerpt of the software demonstrator under development. Finally, in the last section, the results of this contribution are summarized, and an outlook on ongoing research and evaluation steps is given.

2. State of the Art

2.1. Strategic Product Planning

Strategic product planning forms the basis for subsequent product development and describes the process from identifying future success potentials to defining a development mission through foresight, product identification, and business planning (Meyer et al., 2020b). It is typically based on hypotheses about current and future customer needs (e.g., frequency of use of a function). Market research methods are primarily used to determine and test these hypotheses. In contrast, the analysis of technical operating data allows much more precise conclusions to be drawn about the actual use of products by customers, and the knowledge gained can be profitably used for strategic product planning. For example, in product generation planning, which in mechanical and plant engineering is based primarily on existing predecessor systems, it must be clarified whether a rarely used product function is no longer be offered at all in the following product generation or only at a surcharge (Albers et al., 2015).

Furthermore, because machinery and plant engineering goods are capital goods characterized by long periods of use and large investment volumes, existing, obsolete systems are often not simply replaced with new systems. Consequently, product optimization in operation (i.e., retrofitting) occurs. For example, individual parts of a product are replaced or upgraded to add new functions and features that the product did not have when it was manufactured to improve product performance (Kruk, 2011).

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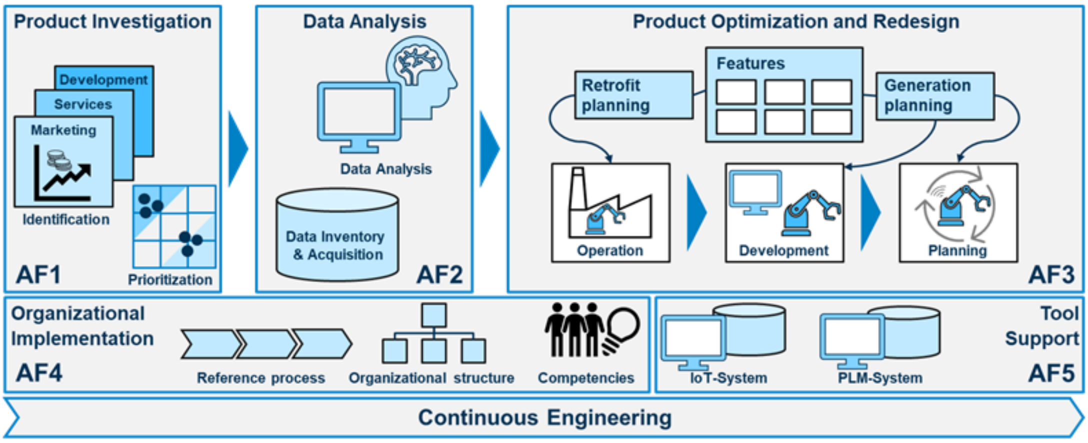

Figure 1. Action Fields of the DizRuPt Project (own representation based on HNI 2018)

2.2. Product Lifecycle Management

While global markets, distributed development, rising complexity, and digitalization are challenges for today's industry, customers require shorter development cycles while maintaining high product quality. In order to allow an effective and efficient development, data and process management throughout the entire system lifecycle is necessary by providing the right management concepts and IT solutions (Gilz, 2014). Therefore, Product Lifecycle Management (PLM) represents a central concept for managing and providing product-related data and processes across the entire product lifecycle between enterprises, suppliers, and customers (Eigner, 2021). As a strategic management approach, PLM has become one of the key technological and organizational approaches and enablers for the effective management of product development and product creation processes consisting of integrated methods and tools for the cooperative generation, management, and application of all product-relevant engineering information (Abramovici, 2007). PLM accompanies the company's products from the initial idea, through the finished product to their end of life, as effectively as possible and aims to maximize the value of current and future products for both the user and the capital owner (Stark, 2016). Furthermore, as the data backbone of a company, the PLM system pursues the goal of being a central data source with access to all IT systems that exist in parallel and thus always providing all users with up-to-date data by being the single or the collective source of truth.

2.3. Internet of Things and the Digital Twin

The Internet of Things (IoT) and the digital twin are central digital transformation concepts. IoT is defined as an ecosystem that includes things (networked dedicated physical objects that contain embedded technology to sense or interact with their internal state or external environment), communication, application, and data analysis to achieve a benefit of some kind (Gartner, 2014). The digital twin, as a virtual image of a device in the field, on the other hand, forms the link between field data (system environment, construction status data, technical condition, operating data), service information, analysis models, and development data (e.g., product data, parts lists, documents, process data) (Göckel and Müller, 2020). The concrete form of the digital twin depends on its use cases and business models in the various application areas, so a variety of definitions have been introduced and constantly refined in recent years (Negri et al., 2017; Stark and Damerau, 2019; Göbel and Eickhoff, 2020). Regardless of the definition chosen, digital twins are part of the architecture of IoT solutions, as they define the access from the application level to the information logistics. The feedback of gained findings into product development in Closed-Loop Engineering supports fast product improvements and strategic product planning (Göckel and Müller, 2020).

3. Closed-Loop Engineering Approach

In order to enable data-driven product planning in today's companies, it is of enormous importance to clarify the question of what data is necessary and relevant, how to get access to the data, and how can

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data consistency and traceability be ensured? In order to answer these questions, a technical concept was developed and prototypically implemented. It links the data management systems for product planning and development (PLM) and product operation (IoT). Also, it ensures complete data continuity across all phases and data objects in the sense of a closed-loop. The resulting Closed-Loop Engineering approach (Figure 2) can be divided into the following four phases described in more detail below:

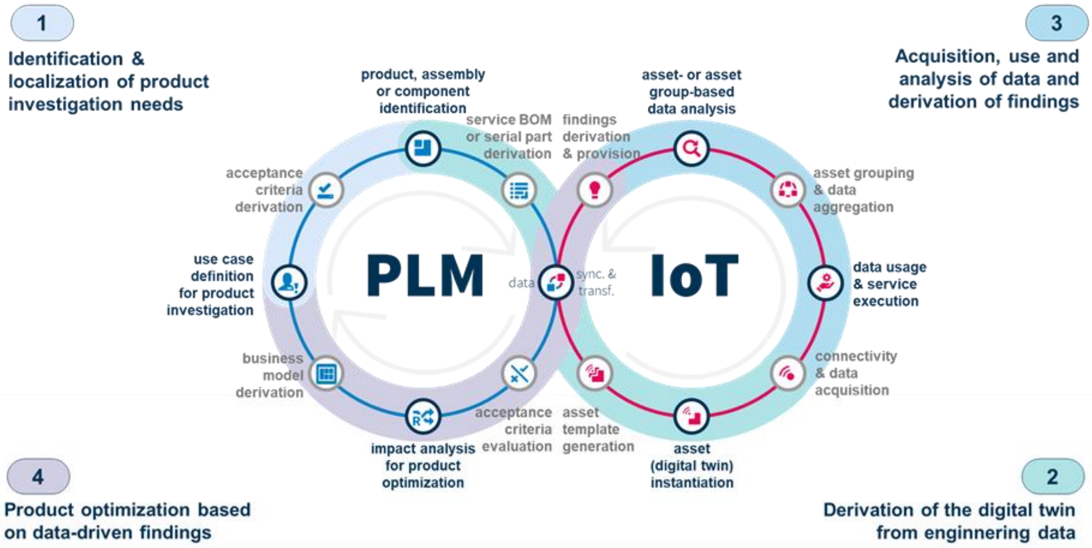

Figure 2. Closed-Loop Engineering Concept for Data-Driven Retrofit and Generation Planning

Identification & localization of product investigation needs

The first phase, "Identification & localization of product investigation needs," includes the problem analysis and localization (Figure 2-1). Based on the definition of use cases built on known problems and optimization potentials, assumptions are made, pointing to possible causes or solutions. Depending on the product complexity, use cases and assumptions refer to the overall system, corresponding assemblies, or individual parts and must be linked accordingly concerning traceability on the data side. For a data-driven evaluation, it is necessary to identify corresponding acceptance criteria per defined assumptions. These can also refer to the entire product or partial aspects.

A methodical procedure for determining use cases and associated assumptions in the context of the product investigation is described by Meyer et al. (Meyer et al., 2020a). The management of use cases and assumptions in the PLM system, on the other hand, can take place via specifications. By using appropriate mechanisms of the software system, individual use cases or their assumptions can then be linked to the managed parts of the product to create data consistency.

Derivation of the digital twin from engineering data

Today, operational data can be collected and monitored in a wide range of different IoT systems. However, in addition to the necessary retrofitting and connecting existing machines, it is challenging for small and medium-sized companies to put the data acquired in operation into the context of their product data and control business applications on this basis. A reason for that is that companies often have inaccurate or no information about the current state of their products in the field (as-maintained). To generate added value for users and manufacturers out of the field data, the second phase of the Closed-Loop Engineering approach describes a procedure to derive a digital twin (an asset in the IoT context) from the PLM product structure (Figure 2-2), to ensure data continuity from the development (as-designed) and production stages (as-built) to the operation stage of the product (as-maintained).

The DizRuPt research project proposes two ways based on the bill of materials (BOM) structure and a serialized part, which instantiates a product variant from the generic product on the PLM side. Accordingly, the second path results in a one-to-one mapping between the serialized part in the PLM system and the asset in the IoT system. Both objects thus describe a digital twin of a specific product but managed in different data management systems and for two different phases of the lifecycle. On the

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other hand, the approach via the BOMs is the more general one. Here, a so-called service bill of materials (sBOM) is first derived from an existing engineering bill of materials (eBOM) (Figure 3-1).

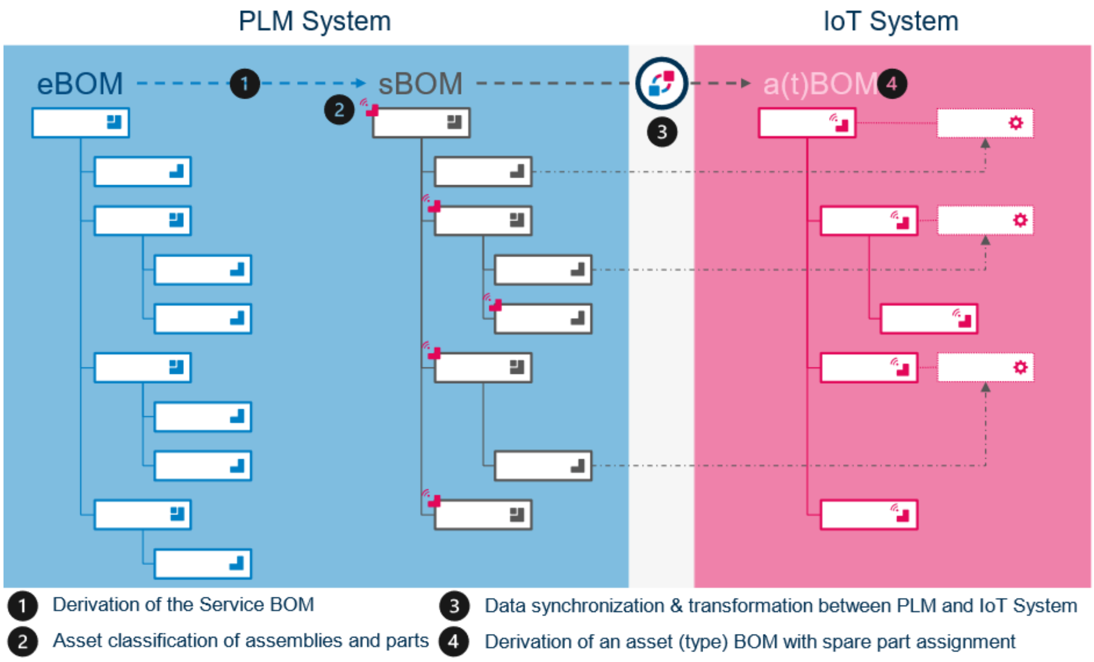

Figure 3. The concept for the derivation of asset structures from engineering BOMs

This sBOM corresponds to a breakdown of all service-relevant parts of a product while it is in operation. Based on this, the next step is to classify the individual parts of the sBOM in terms of building an asset structure (Figure 3-2). Here, identification occurs, which product parts should be represented as separate assets so that field data can be managed and business applications can be executed. Secondly, which parts are crucial for service as spare parts. When the sBOM changes to a certain status, synchronization with the IoT system occurs (Figure 3-3), and the sBOM is transformed into a so-called asset type BOM (Figure 3-4). Asset type BOMs reference a virtual product model in the PLM system and extend it with IoT application-specific aspects, e.g., those for event and telemetry data processing during product use. Assets are then instantiated using a template mechanism from the asset type and its component structure. Therethrough, assets also reference the virtual product model of their respective type. Finally, with the creation of the asset and an additional, possibly necessary, upgrade of the products in operation to make them IoT-ready, the transition to the next phase of the Closed-Loop approach starts.

Acquisition, use, and analysis of data and derivation of findings

The third phase, "Acquisition, use, and analysis of data and derivation of findings," deals with the further processing and managing of product data from operations (Figure 2-3). In addition to telemetry data, which can be continuously stored and processed in a time-series database, events can also be generated with precise time values. Events are bidirectional and can be generated automatically from the product, transmitted to the IoT system, or created directly in IoT. Events generated in the IoT system can be executed manually or executed automatically by referencing existing values from the time series databases or by time-based rules. Triggered events can drive operations and processes related to both business applications in the IoT system (e.g., the creation of service cases or new business objects) or the products in the field. An example here could be the query of the current hardware and software versions or the specific control of certain product functionalities.

Based on the existing data from the field and product development, new information about the product can thus be generated. The pool of data for analysis is constantly growing and increasing in quality. The data analysis procedure and the IT infrastructure required for this depend on the existing data, the corresponding use case, and its objective. For example, key performance indicators in a descriptive data analysis can be done directly in the IoT system based on the collected telemetry data. In contrast, for anomaly detection in the sense of exploitative data analysis, third-party tools may have to be connected.

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The collected data are provided as a basis for model building. Optionally, only the results of an upstream analysis (e.g., on an edge device) can be transferred to the asset in the IoT system, managed, and further processed. In addition, IoT platforms should enable combined assets into groups or fleets to obtain a broader database from product operations. This database can be significant for later product generation planning. For this reason, insights gained from utilization can relate to both individual assets and asset groups. A corresponding methodical procedure for the use of data analyses in the context of strategic product planning is given by Massmann et al. (Massmann et al., 2020).

Product optimization based on data-driven findings

In order to generate added value for product planning and the subsequent further development of the product, the product knowledge managed in the IoT system must also be made available in the corresponding data management system for planning and development. The last phase deals with the feedback of the findings into the PLM system and their processing (Figure 2-4). The referencing between the virtual product (PLM) and the asset type (IoT), or between the serialized object and the asset, ensures traceability between the data objects so that even if the findings from the IoT system are synchronized in the PLM system, it is clear which PLM object they refer. Thus, the generic product or its specific serializations are linked to the product operation findings and the product investigation's acceptance criteria, which the data of the findings can evaluate. For example, suppose the assumptions of the product investigation use cases can be confirmed by the data-driven evaluation of their acceptance criteria. In that case, the corresponding product can be prepared for optimization and transferred into the planning phase. In the process, the impact on the product data can be analyzed through the continuous linking of the various pieces of information in the PLM system. A corresponding engineering change can be initiated. In addition to the impact analysis and the optimization effects for the new product generation or the retrofitting of products already in use, new business models can also be derived from the knowledge gained, or assumptions made in this regard can be confirmed and substantiated. An overview of the necessary data objects required for the described Closed-Loop Engineering approach for strategic data-driven product planning, and their interrelationships, is given in Figure 4.

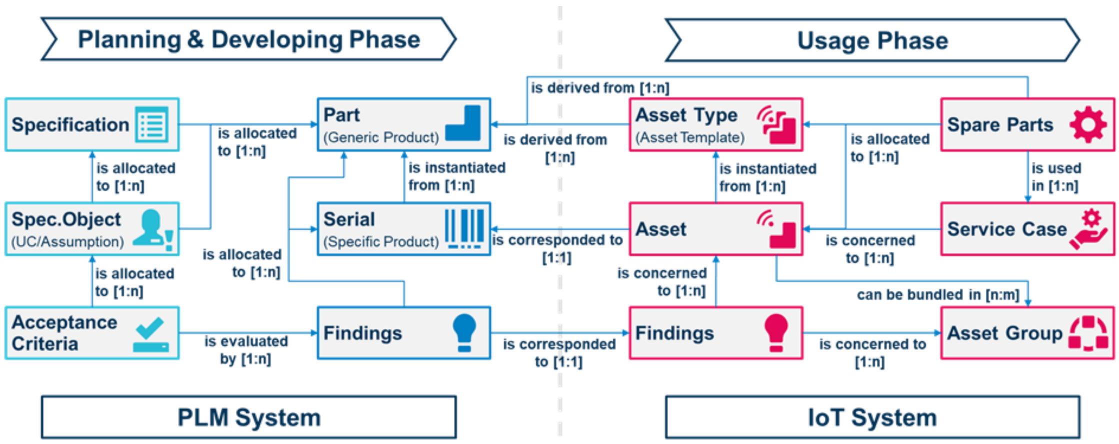

Figure 4. Data objects of the Closed-Loop Engineering Approach

4. Pilot applications for validation and evaluation of the approach

The concepts, methods, and tools developed within the DizRuPt project are validated through four pilot applications with different focuses in the industry branches of ventilation systems, connectivity and automation technology, self-service transaction systems (ATMs), and hydraulic forging hammers. The Closed-Loop Engineering (CLE) approach presented as part of this contribution is addressed by the scenario of a Fieldbus coupler device from the connectivity and automation technology industry branch. Fieldbus couplers support system integration in automation technology by connecting sensors and actuators (field devices) in the production process with programmable logic controllers (PLCs) to enable automation and ensure data consistency.

As part of the project, the company manufacturing the Fieldbus coupler defined two assumptions for product improvement, the investigation of which the CLE approach can very well support:

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1. It was suspected that the operating temperatures range of the device is too narrowly defined. Therefore, the product is unnecessarily excluded from consideration in more adverse climate conditions applications.
2. It is suspected that Fieldbus couplers are frequently modified in terms of connected sensors and actuators during their operation. If this is true, customer service and additional services can be offered to customers to improve reliability and reduce the chance of misconfiguration.

Both assumptions can be proven true or disproved based on the analysis of field data if they would be available in the necessary quality and quantity. Therefore, a Closed-Loop Engineering demonstrator for data-driven planning and improvement was developed to show how the CLE process can be implemented in a managed software solution. From product investigation, data acquisition, processing, and analysis, to the findings making, assumption assessment, and planning of product improvements. From a technical point of view, the demonstrator consists of a physical part – the Fieldbus coupler and eight I/O modules and a custom, retrofitted gateway – and a virtual part – an integrated software platform for Industrial IoT ("Elements for IoT") and Product Lifecycle Management ("CIM Database") based on a modular solution kit by CONTACT Software Ltd., Germany. Figure 5 shows the demonstrator's physical setup alongside the virtual software parts, explained in the following.

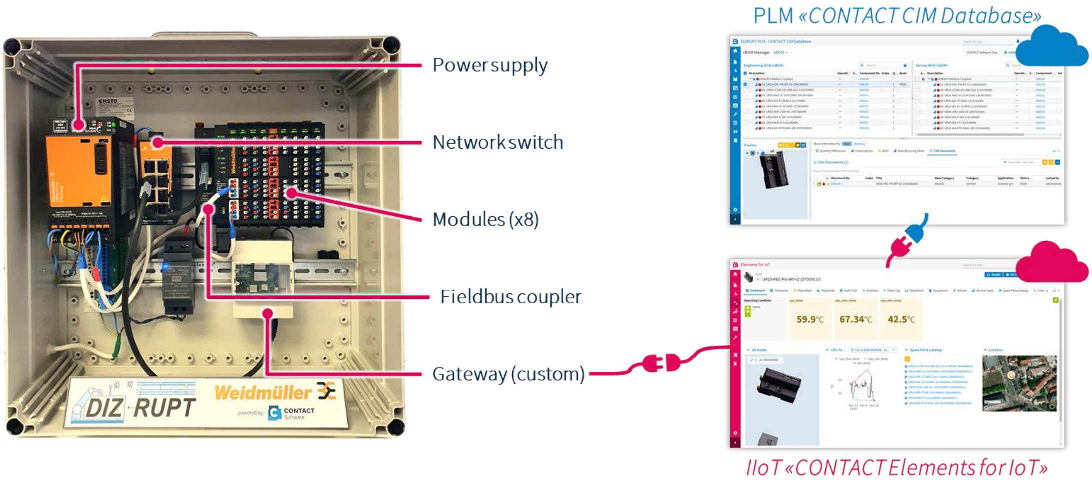

Figure 5. Physical setup of the CLE demonstrator based on a Fieldbus coupler

Figure 6 illustrates the software implementation of the demonstrator for data-driven product improvement consisting of a PLM solution, which serves the need of engineering and product planning, and an Industrial IoT solution (IIoT), which covers the usage of the product documenting its physical configuration and collecting usage data. Following the research project's approach, the product assumptions were first defined in the PLM system using the appropriate data model class, therefore – a specification linking it to the product representation in PLM. Concretizing the assumptions by acceptance criteria was further conducted (Figure 6-1). In order to represent the product with its structure in the IIoT system, it was necessary to derive a template (not shown in the image) for digital twin instantiation based on the virtual product model available in PLM. Multiple virtual assets representing actual devices in the field can then be instantiated in IIoT from the asset type. To facilitate this, first, a service bill of materials (sBOM) was derived from the engineering bill of materials (eBOM, part of the virtual product model). Second, asset-relevant components were classified for inclusion in the virtual asset's component structure in IIoT. Finally, synchronization between PLM and IIoT instantiated an asset with all relevant information present in PLM or supplemented into the template. Through this, an automated virtual asset instantiation process from engineering data of the virtual product model was implemented. The logic for instantiation can be altered based on the concrete use case. For example, different BOM items may be classified as relevant for asset component creation. Other parts might not be relevant for the asset structure but may need to be made available and managed as spare parts to be used on service cases that arise later (Figure 6-2).

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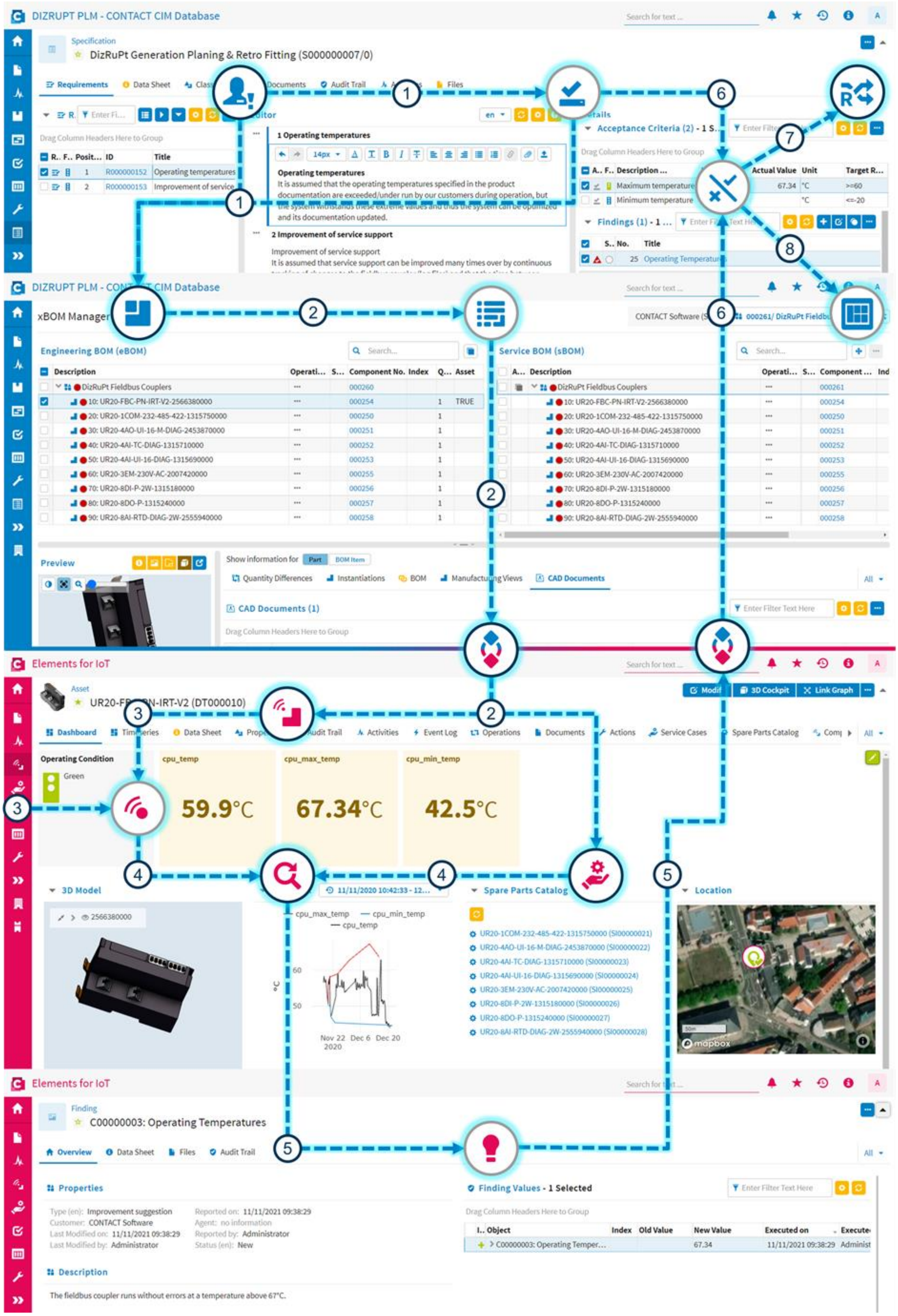

Figure 6. Implementation of the closed-loop engineering approach in CONTACT Elements

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A flexible, integrated data model and the configurable interface between PLM and IIoT allow for implementing different instantiation logic and synchronization processes. As soon as the virtual assets have been created in IIoT, physical field devices can be connected to the system through standard protocols such as MQTT or OPC UA; field data can be collected, managed, and processed (Figure 6-3). The collected data can be visualized, used to trigger service cases, or serve as a basis for the analyses of proving or disproving the previously defined assumptions. The analyses can be performed on individual assets and fleets of the same assets types. The results can be managed, visualized, and processed to performance indicators, such as the maximum and minimum temperature under which the Fieldbus couplers operate without failures (Figure 6-4). Based on this information, findings can be derived and synchronized from IIoT to the PLM for further product planning and optimization (Figure 6-5). In addition to that, the achieved data continuity and traceability allow for knowledgeable evaluation of the assumptions. E.g., the insight object is linked to the virtual product model and can then be used to evaluate the acceptance criteria of the product assumptions (Figure 6-6). The current example showed that the Fieldbus couplers could operate without errors at higher temperatures than defined, which means that the acceptance criterion was automatically evaluated positively. Once all criteria and thus also the product assumptions have been evaluated, the product optimization process can be triggered by an engineering change in PLM (Figure 5-7). The availability of operational data and the insights generated with their help may even allow for new business models driven by data (Figure 5-8).

5. Conclusion and Outlook

Combining the concepts of PLM and IoT, this contribution introduced a closed-loop engineering approach for data-driven retrofit and generation planning. A key objective of this approach is to ensure data consistency and traceability. Here, in the PLM system, the assumptions from product planning are linked with the virtual product model from development, and templates for the digital twin in operation are derived from this. Next, the digital twins are instantiated in the IoT system, and operating data is recorded, processed, and analyzed. Finally, the findings gained are transferred to the PLM system to evaluate the product planning assumptions. Then, system optimization can be executed based on this or new business models derived. The concept represented here describes a general procedure, which was exemplified using one of the four pilot applications of the project. However, the procedure can also be modified and extended depending on the application.

In the project's further course, the concept for data integration and networking shown here will be linked with the reference process being developed in parallel and its steps for organizational implementation to enable integrated data and process management for data-driven strategic planning.

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