Cognitive Decision Support for Industrial Product Life Cycles: A Position Paper

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***Abstract*—Current trends in manufacturing lead to more intelligent products, produced in global supply chains in shorter cycles, taking more and complex requirements into account. To manage this increasing complexity, cognitive decision support systems, building on data analytic approaches and focusing on the product life cycle, stages seem a promising approach. With two high-tech companies (world market leader in their domains) from Austria, we are approaching this challenge and jointly develop cognitive decision support systems for three real world industrial use cases. Within this position paper, we introduce our understanding of cognitive decision support and we introduce three industrial use cases, focusing on the requirements for cognitive decision support. Finally, we describe our preliminary solution approach for each use case and our next steps.**

Keywords–Product Life Cycle; Validation; Big Data Value Chain.

I. INTRODUCTION

Manufacturers are experiencing the request for ever more intelligent products in shorter cycles from their customers. At the same time, manufacturers are also facing increasing cost pressures from global supply chains and increasingly complex regulatory requirements. Consequently, a holistic view of the Product Life Cycle (PLC) is a necessity to analyse and to manage these conflicting requirements. PLC management considers information describing the design, development, validation, production, usage, maintenance and disposal phase of a product. The collected data from these stages is not limited to data directly related to the design of the product, e.g., specifications, or material usage. Moreover, it includes aspects related to the product (e.g., change orders, procedures, suppliers, workflows, etc.), as well as aspects related to the product (e.g., change orders, procedures, suppliers, or workflows) [1] [2].

Collecting this data is a first step. Importantly, the data provides the opportunity to extract valuable knowledge from it to derive insights significant enough to trigger improvements on any stage of the product life cycle. Hence, data analytics approaches can help to extract actionable knowledge from the data, laying the foundation for a better understanding of the involved processes. Depending on the complexity, coverage and scale of the product and its life cycle, the extracted knowledge can be complex and manifold. Decision Support Systems (DSS) are intended to refine and present the extracted knowledge, since they select the right information for a person working on a particular task in a given stage of a product life cycle [3] [4]. Based data analytic approaches they are also named data driven DSS [5].

This paper reports from research efforts of a consortium formed by industry and academia to tackle this challenge, specifically, the research center Pro2Future and the industrial partners AVL LIST GmbH (AVL) and Fronius International GmbH (Fronius). Both industrial partners aim to leverage the potential of cognitive DSS based on data analytic approaches. AVL and Fronius are already adopting the Internet of Things (IoT) paradigm by creating connected products, which are constantly collecting data about their usage. This creates the option of new data driven approaches towards cognitive DSS, which we investigate in three different use cases. Each of the use cases offers the option to research various aspects of cognitive DSS, applied to a specific application domain. Due to the importance and the complexity, we investigate novel approaches outlined in this paper. The strategic goal of this joint project is to investigate the potential of cognitive DSS in the context of the PLC in industry.

This paper is organised as follows: The second section gives a brief overview of research conducted in either cognitive DSS and the product life cycle. The third section describes three use cases on how engineers can be supported in their work by DSS. Based on the use cases, the forth section discusses difficulties in integrating such systems into the industry, whereas the last section gives an outlook for future work of the three use cases separately.

II. BACKGROUND

A. Cognitive Decision Support Systems

The overarching aim of decision support is to give users the support for making better decisions [6]. Decision support is particularly relevant for complex decision making problems,

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where human deciders cannot process all relevant data in time and in full detail for the decision, due to data volume, velocity or complexity. Current developments, including IoT or Industry 4.0, lead to an overwhelming amount of data available for decision making [7]. Consequently, the demand for decision support, during the whole decision process, also increases [5]. To handle the complexity and volume of such data driven decision problems, the decision making needs to be supported by Information Technology (IT) [8].

DSS aim to help decision makers in utilising data and models in solving unstructured or semi-structured problems, to improve the decision quality [10]. A common approach focuses on understanding the decision problem first, and then breaks down the decision-making process into several sub-processes [11]. These smaller problems can then be addressed by mathematical or algorithmic solutions [12], after the decision has been structured [13]. The disadvantage of this "classical" DSS is, that they are designed for one specific decision problem and that it is difficult to adapt them to new or changed decision problems [14]. However, the digitisation of industrial processes demands a high level of adaptability and flexibility [15]. Hence, more flexible and cognitive approaches, applicable to huge data sets with varying properties and inherent format variety, are needed [16].

Cognitive computing, in general, aims to develop coherent, unified, universal mechanisms, which are able to adapt to new situations and are inspired by the human mind [17]. More specifically, cognitive systems rebuild aspects of human thinking while adding the ability to handle big data sets [18]. Especially, the ability to handle big data sets is crucial for the new emerging data-based decision problems. In the scope of DSS, a cognitive system can give contextual insights from the model, which is able to generate hypotheses in terms of giving possible explanations, and to continuously learn from the input data over time [14]. Summing up, in the context of our work we define:

Cognitive DSS provide universal mechanisms capable of adapting to changing data sets, to improve the decision quality. Thereby, universal mechanisms refer to the ability to continuously learn from the input data and to generate hypotheses based on this learning. Improvement in the decision quality means, that cognitive DSS present insights from big data sets to decision makers in such a way, that the decision quality increases.

B. Product Life Cycle

The PLC is a process describing stages of a product from conceptional design, over production and usage, to the end of life [2]. Due to the so-called forth industrial revolution, *big data* plays an increasingly important role in the modern industry and offers potential benefits for several industry sectors [19]. The usage of data can create value for industry in many ways including increased productivity, better product quality and higher competitiveness, on both the customer and company side [20]. Since each of the process stages are independent, it is necessary to implement a data-value chain for each of the product life cycle stages separately [21]. Figure 1 depicts the relation between the PLC, the big data value chain and how data and knowledge are exchanged between the two processes [9]. This work picks up on these ideas and focuses on the data usage process for the PLC validation stage, the production stage and the in-use/service stage.

III. USE CASES

The following use cases explain data usage in several stages of the specific PLCs of our industry partners, implementing cognitive decision support in different ways.

A. Powertrain Verification and Validation

1) Context: An important aspect of AVL's engineering services is the Verification and Validation (VV) of powertrain prototypes for automotive applications. This VV activity follows the development stage in the PLC. The use case introduced by [9] describes how data usage for VV can be implemented. Verification is a quality assurance process to provide that the product fulfils its intended requirements [22] ("Having developed the right product"). Requirements can be driven by user needs (e.g., fuel or energy consumption, engine performance and durability), but also imposed by legal requirements (e.g., noise emission) [23]. Validation asks, if the intended functionality can be provided over the product lifetime ("Having developed the product right"). VV for powertrains can be either realised in a testing environment, so-called testbeds, or in a customer usage-oriented test, based on customer-oriented usage profiles (e.g., on road). During such tests, hundreds of sensor signals are collected from the powertrain operation as a function of time and/or powertrain controls, like throttle control. These sensors provide data about e.g., engine temperature, exhaust gas composition, pressures, torque and other engineering parameters. Depending on the purpose of a specific VV target, those tests can take thousands of hours for every tested prototype instance under controlled conditions, leading up to a tremendous amount of data. The following use case is located in the early VV stage of the PLC and focuses on functional requirements (mainly verification), but also durability requirements (mainly validation) of an automotive engine. The tests investigated in this use case are all conducted on automotive test beds, where the engine is operated at predefined load conditions.

2) Problem Description: A main challenge in powertrain testing is to support engineers in assessing the condition (health) of engines from large amounts of sensor measurement data taken during test cycles. Many parameters (channels) are measured during testing. A channel contains a value (also called sample point) typically every 100 ms which corresponds to a 10 Hz sample rate, but can have sample rates up to multiple kHz. Depending on the test setup, up to hundreds of channels can be recorded. It is a challenge for engineers, working with this data, to observe every channel and to extract relevant information from it. Depending on the test case, channel measurements may be noisy, or external events may happen which only get captured indirectly in the measurements. As a simple solution, engineers manually select a number of channels based on experience, and define thresholds for simple anomaly detection [24]. The challenge of this approach is, that the thresholds for each sensor need to be defined manually, based on individual experience. This can be done by experienced engineers for some well-known sensors, but not for all sensors. Furthermore, there are complex relationships between the channels, involving correlations and lead-lag relationships, as they are not independent from each other. DSS for powertrain

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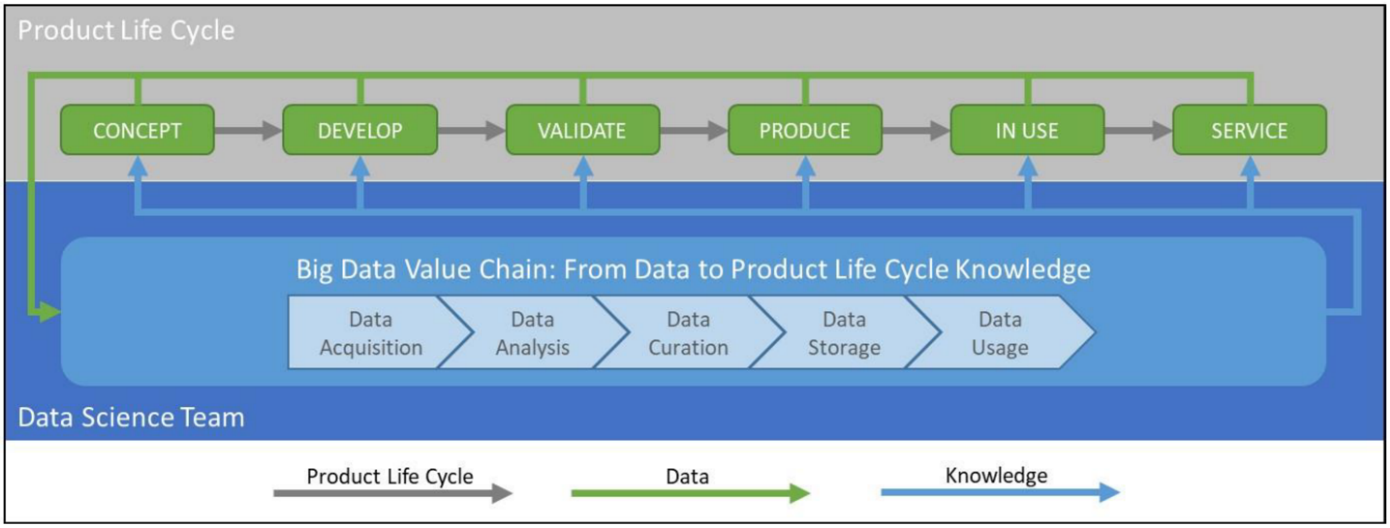

Figure 1. Transfer of knowledge between product life cycle stages and big data value chain by [9].

testing needs to help the test engineer in monitoring relevant channels, guiding her or him to relationships and anomalies as they occur, and predict possible failure cases early on for test intervention, if needed.

3) Solution Approach: Powertrains are increasingly complex systems and the know-how of domain experts is an indispensable resource for a condition monitoring system. Research on time series analysis has provided numerous algorithms to detect trends, patterns and outliers in data [25]. We follow an approach based on interactive visual data analysis (or visual analytics). The idea is to combine data analysis algorithms with appropriate visual representations, from which the expert can efficiently perceive patterns found by the algorithms, and by which he or she can interact with model parameters, and drill down into data details for confirmation and exploration tasks. Visual analytics applications for industrial sensor data have been developed for several applications recently. In [26], a general approach for industrial sensor data has been proposed. [27] focuses on predictive maintenance in the production stage and [28] focuses on the in-use phase of the PLC, describing more specific solutions. The SignalLens system [29] allows to monitor large time series using an efficient focus-and-context visualization and representing features of interest to guide the visual inspection by the expert. Approaches such as these, aim for scalability of the analysis with large amounts of data. In general, it is promising to combine the strengths of human experts (background knowledge, abstract problem-solving, etc.) and of computational data analysis (e.g., fast algorithmic search for well-specified patterns in large data) [30]. To visualise time-dependent data several promising techniques exist, including HorizonGraphs, RiverTheme Graphs or Heat Maps [31], which could support the expert in exploring large amounts of sensor data.

In addition to the visualisation techniques, computational models can be trained for classification, regression, clustering or pattern recognition. Since engineers can have a better understanding about the involved processes and parameters, they should be supported in distinguishing between rare events and true anomalies. In an unsupervised machine learning scenario, the engineer can be supported by visually highlighting potentially interesting outlying data and data patterns which occur frequently. Based on such comparison, the engineer can decide if an anomaly is relevant and needs further inspection, or is transient. We are currently experimenting with showing composite anomaly scores for a sequence of test cycles. By comparing the measurements between cycles, experts can quickly recognise larger differences in measurements, hinting at possible anomalies for further inspection. Figure 2 illustrates a glyph-based design to visualise anomalies in industrial test cycles. It aggregates two different algorithms for anomaly detection (top and bottom circular sector) and encodes the anomaly scores by the intensity of red for visual perception of humans. This design can be adapted for other datasets, as long as they are collected from cyclic data, since those cycles has been identified to be suitable as the granularity level for data visualisation and analysis. However, cyclic data is reasoned by the repetitive behaviour of many industrial tasks. Therefore, the concept could be applicable on other industrial domains as well.

The interaction of a domain expert with the visualisation can be learned by the model in terms of parameter refinement and future decision support. This learning of domain expertise in a cognitive model is also the key to make the desired DSS, based on visual analytics, cognitive. At the end of the workflow new knowledge is discovered, can be applied to new products and lead to a constantly improving condition monitoring system.

B. *Welding Machine End Of Line*

1) Context: The Final Test System (FTS), at the end of the manufacturing process, is a crucial stage concerning the PLC. In our application, every produced device must accomplish a successful quality check by the FTS before it is sent to the customer. In other words, each produced device has to undergo a quality test as a final inspection by the FTS.

The FTS fully automatically measures about 300 different parameters and the process is supervised by an experienced employee. For the test, three possible results are specified:

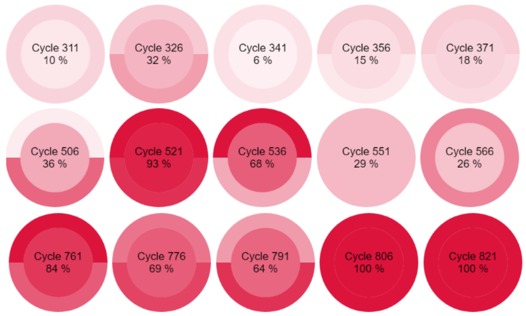

Figure 2. Glyph-based visualisation of anomaly scores. The outer segments show different anomaly scores, while the center shows an aggregate score.

Firstly, the device passes all measurements in the first run. Secondly, the device passes the test successfully after multiple iterations of the test and revisions. Thirdly, the device fails, even after possible re-takes of measurements. In the first and the second case, the device is declared to work properly and is ready for shipping to the customer. In the third case, the device will be handed over to the repair centre for further investigations. Hence, the FTS collects a large amount of data about the devices and their conditions when passing or failing the test.

2) Problem Description: When a device has an incident, which cannot be solved by the customer, no FTS is at hand to investigate the actual cause of device failure. Instead, a maintenance procedure is started, and a repair team is sent to the customer to identify the cause of the failure. Once, a diagnosis is made the identified parts causing the failure will be replaced with new ones.

This diagnosis process is not trivial, since the repair team is obligated to recognise the cause direct in the field with far less sophisticated equipment than the FTS. The process of failure identification is complex and requires a knowledgeable and experienced repair team as the amount of the reliable information is small. Moreover, if the failure cause is unknown, also the needed resources (e.g., spare parts and repair time) cannot be known in advance. But particularly in our case, the number of products in the field and especially the product variants are very high. Therefore, the repair team often needs to anticipate the required resources in advance, which is time-consuming, error-prone and in turn, leads to higher costs. The objective is the creation of a cognitive DSS, which analyses the FTS data and provides decision support for the repair team in the field. The DSS should use the identified knowledge from production data to identify possible failures, based on the known device behaviour and to recommend suitable repair strategies. This system should learn from past cases, improve over time by feedback and be able to transfer the learned to new products or product variants.

3) Solution Approach: The process of the final inspection is complex regarding both the significant number of measurements and the variety of variants and options, respectively. This means, that there is only a small set of comparable measurements throughout all devices. This reduces the amount of usable data and makes the learning more difficult. Only for a small set of common device features, there is a large volume of data, but for the different options and variants there is only a small sample available. Moreover, to provide solutions that reflect the reality it is essential to consider the interdependence between multiple components required to assemble the system. Therefore, considering multi-component system challenges [32] [33] and handling these properly could grant advantages. By employing advanced applied machine learning approaches (e.g., unsupervised learning methods [34]), common behaviour amongst different variants and options can be recognised. Next, rule-based machine learning methods [35] will be applied to identify associations within the maintenance data. This step will extract additional knowledge about the service activities, which will also be incorporated in the DSS. Finally, apply acquired knowledge to recognise failures also in previously unseen devices with similar error patterns, thus supporting the repair team. Moreover, this approach will adapt the learned parameters by incorporating the new knowledge gained from the upcoming data leading to a cognitive DSS. The DSS is therefore capable to aid the worker in the field by predicting the failure causes. Hence, the repair team can better plan the needed resources thus reducing the repair costs.

C. Welding Machine Maintenance and Service

1) Context: In a modern industrial welding process, maintenance actions are required to keep the process operating at its optimal conditions. Within the welding devices, multiple sensors are integrated providing a condition monitoring of process critical parameters. Commonly the monitored parameters include information about the voltage, current, or power of each individual welding. Furthermore, information such as the configuration settings of the welding device, identification numbers of the welded component, etc. are also collected during this process. While the collection of this process data is commonly automated, collection of data about the maintenance actions taken, often require the involvement of workers. For an immaculate data collection, a data collection system is provided, which protocol the maintenance action performed on the welding device. Due to the involvement of the worker during this process, this data collection is more laborious and error-prone compared to a fully automated data collection.

2) Problem Description: A common maintenance procedure is conveyed by monitoring the welding device in-use by multiple integrated sensors. The readings from those sensors can identify the possible need for maintenance actions of various components, like changing the contact tip, cleaning the air filter, etc. These necessary maintenance actions are conducted by a worker in the manufacturing process and the execution of the maintenance action is recorded. The benefit now lies in the combined recordings of the welding processes' parameters and the recorded maintenance actions. The objective is to support the user in finding the perfect time to conduct a specific maintenance activity so that the productivity and quality of the welding process is optimal balanced. The cognitive DSS analyses the process and maintenance data to identify possible patterns within the data. These patterns are used to assist the worker by recommending suitable maintenance activities.

The main challenge in the creation of the cognitive DSS is the automated detection of the need for maintenance activities, based on data-driven solutions, considering the variety of variants and options. The product variants and options make almost all devices different, hence also potentially requiring different maintenance actions. These systems consist of multiple components, which are non-identical and dependent on each other, leading to a multi-component system.

This high variety decreases the amount of data remarkably regarding individual systems (variants and options), leading, on the one hand, to a huge amount of data on the base core of variants, and on the other hand, to small amounts of data concerning the specific variants or options.

3) Solution Approach: Both, the small data challenge and the various dependencies within multi-components need a careful handling while preparing the data. Next, the knowledge extracted from this data is used to improve the cognitive DSS, which in turn will support the workers during the decision-making process. Thus, to increase both the reliability and the performance of the devices, we propose one approach based on data mining techniques [36], such as temporal pattern mining [37] and supervised learning methods [38]. First, assuming that various variants and options are not entirely different, the aim is to identify a relevant variant by applying exploratory data analysis methods [39]. In this case, the aim is to deploy a solution for a specific variant, or subgroup, and later generalise it over all variants and options. Second, recognise patterns (e.g., temporal patterns), within the process data, and relate them to maintenance actions. Third, use the extracted knowledge from previous step, to predict perfect timing for maintenance actions. Finally, improve the prediction accuracy by considering the interdependences between components. Moreover, the DSS will learn from the actions taken and update the optimal maintenance relevant parameters regarding each component separately, leading to the creation of a dynamic optimal maintenance activities strategy over time.

IV. Discussion

The success of the project highly depends on the acceptance of the proposed cognitive DSS by the involved employees. To ensure this, we involved the potential end users from an early stage onward consciously in the project applying a participatory design approach. One important aspect to engage the end users was that the cognitive DSS is designed to support the human experts, and not to replace them [5]. Also, both our industry partners are convinced that, in the foreseeable future, humans cannot be replaced in their core processes, but need more support as work tasks become more complex. The cognitive DSS provides assistance and support by presenting insights from the analysed data, so that the domain experts can develop a better understanding of the PLC. This is an opportunity for the companies and their customers alike by improving productivity, product and support quality and, hence, increased competitiveness.

The participatory approach is not only applied during the design and roll out of the first version of our cognitive DSS itself, rather it was also very important to collect and clean the data in a participatory way. The strong engagement with the end users was necessary to build the required domain knowledge and to receive high quality feedback. This engagement created awareness of the fact, that the quality data collected during the execution of the PLC determines the decision quality and thus is the secret to the success of the DSS. The DSS can only be as good as the data it is built upon. Hence, the end users need to understand that data collection is a key activity and not only another administrative duty. Relying on strong awareness building activities, we developed well-defined data capturing processes for collecting relevant process and quality data from the end users. In doing so, we capture domain knowledge to improve the DSS over time and closing the feedback loop between the PLC and the DSS by two links. Firstly, the data from the PLC going into the DSS and, secondly, the information provided by the DSS to the workers is linked to the PLC. As a result of this cognitive element, users benefit by improved decision support in return for their efforts they spend in data collection activities.

All use cases deal with complex multi-component systems, or even systems of systems creating an immense complexity by all interactions and connections between the components. Such complex systems need to be divided into smaller parts to handle the complexity in a meaningful way. The proposed multi-component analysis is doing this by the individual estimation of the component's wear, modelling interdependences between components, and transferring of insights to different but comparable sub systems.

The described project is ambitious, complex and requires a high invest by all involved partners. Thereby, the investment is not primary in software or servers, rather than in human resources needed to achieve the required understanding and awareness for introducing cognitive DSS. This is due to the fact that continuous high-quality feedback from end users is needed to ensure the continuous learning of the cognitive DSS. Despite of these remarkable efforts, the company partners are convinced that improved decision support will pay off. Even more they believe that this is key to be successful in a globalised and digitised world.

V. Outlook and Future Work

We plan to further investigate different promising directions within our industrial use cases described above. Therefore, in this section we briefly discuss the future work on each of the three use cases separately.

A. Powertrain VV use case

It is a common approach in powertrain VV to define test cycles with given engine speed and engine torque over time. In these test cycles, the engine usage is simulated and repeated until the required total test time is reached. For example, in a durability test, such cycles take two hours and will be repeated till the total time of two thousand hours is reached. We base our design idea on the assumption that those cycles are highly comparable and elaborate on this in future research. In theory, all sensors should return similar measurements for constant engine speed and engine torque. However, some uncertainties need to be investigated in more detail. Over time, the measurements of channels can differ by wearing of the powertrain, environmental changes like temperature, exchanging parts, faulty sensors or different undocumented calibrations. Recognition of many of those anomalies should be done by data analysis. For this purpose, we will investigate if test cycles can be defined as a granularity model for the visualisation and the subsequent data analysis approach. This combination seems promising to highlight anomalies and to further identify if the conditions of the powertrain worsen over time. To judge the conditions correctly, the system needs to learn from user feedback so that the systems capture domain knowledge over time. An idea for user feedback is to allow experts to select and label data patterns corresponding to certain events. The labels can be taken as training data to train supervised data analysis methods, e.g., classifiers to apply to new data.

Preliminary findings show promising results in applying correlation-based anomaly detection. In this first version, a visualisation depicts the correlation matrix for every channel combination of every cycle. By subtracting the matrices from the reference cycle's correlation matrix, the deviation of two cycles can be visualised as a heat map. Also, deviating channels can be intuitively identified by engineers and further analysed. Another task for future work, is to investigate and apply several anomaly detection algorithms. Finding the best model, regarding predictability of data, for different applications, is a hard task. Visual analytics offers the capability of engineers to interact with data through information visualisation and the underlying data analysis. Suitable techniques need to be reviewed, and through design studies [40] in collaboration with the end user engineers, further investigated and developed. Consequently, the design needs to be evaluated, whereas pair analytics [41], seems to be a feasible approach to evaluate visual analytics applications.

B. End of line use case

The small data challenge in our end of line use case, i.e., the high variety of products and the small data sets of reference measurements is a challenge for data driven approaches. In the solution approach, we aim to identify common parameters and values behaving similar of all different components of product variants which are comparable. Finding the right level of detail for the multi-component systems in the project is also described as a major challenge in the literature [32]. Our approach based on exploratory data analysis first aims to identify relationships and interdependencies. Next, the aim is to recognise common error and fault indicators amongst different product variants by applying unsupervised learning approaches. Moreover, rule-based approaches are considered to recognise patterns within the available data extracting additional knowledge about the components and the service activities. Lastly, over the time the decision variables will be adapted every time new information is provided so that the DSS learns.

C. Welding use case

The small data challenge also applies to the welding use case. To solve this challenge for this use case, also similarities between individual components and modules are identified with the same means used in the other two use cases. Hence, the first step is to identify relevant variant, or group of variants by applying exploratory data analysis methods. Next, within an appropriate group of variants, so called clusters, machine learning approaches will be performed to extract indicators to predict the wear of different components. These indicators are based on monitoring information obtained automatically and maintenance action logs provided by the workers conducting the maintenance. Both data is jointly analysed by frequent pattern mining approaches to find sequences of maintenance actions on the component and cluster level. Lastly, the learned parameters (e.g., maintenance strategy) will be adapted every time new information describing the current health state of the system and components are provided, respectively. Another important aspect of our future work is to investigate how the insights we gain can be used for process improvement. More specifically, how these insights can be used to improve business processes representing a concrete PLC during design and run time. For this purpose, we want to create an interface to the process management tool CENTURIO developed in the research center CDP [42].

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