Data pipelines for product function prediction in circular factories

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Abstract

Optimizing global material flow and resource consumption is a key goal of the circular economy. Regarding production, the circular economy relies on the targeted reprocessing of used products, requiring extensive product data for informed decisions. However, the available data regarding distinct product generations and variants is fluctuating, and necessary data can be scattered or incompatible. The problem is that a comprehensive data processing method to deal with the mentioned requirements is missing. Therefore, a concept for designing data processing pipelines is presented and demonstrated in a circular factory for angle grinders. These pipelines focus on function prediction tasks and showcase the benefits of adapting pipeline compositions, drawing from existing data analysis.

Keywords

circular economy, data pipelines, functional modeling, circular factory, product development

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1. Introduction

One aim of the circular economy is the optimization of the global material flow and resource consumption by efficiently and selectively reprocessing used products. In a circular economy, the value retention of products through remanufacturing plays an important role [1]. As circular factories produce new products from used subsystems and components of different generations and variants, a linear production process is not feasible. Deciding which subsystems of the products are fit to be reprocessed is particularly challenging due to the uncertain conditions of the returned products. Regarding design research, approaches to ensure quality standards of new products in a circular economy are still missing [2].

During the reprocessing of a single product, the circular factory needs to make a variety of decisions. To generate a new product from used subsystems and components, it needs to decide, how to disassemble, reprocess and combine components, when to recycle components, and when to add new components from linear production into circular production. For reliable decisions in a circular factory, a large amount of data from the area of product development is needed, both in diagnostics of the returning products and in predicting the reliability of reprocessed products. Various data on the product embodiment as well as on its functions and behavior must be collected, combined, and evaluated [3]. However, the data is available in different formats from versatile sources and is often scattered or incompatible [4]. To handle it, a wide variety of algorithms and models is needed. At the, sometimes non-present or insufficient, intersections of these elements, difficulties and losses occur [5]. Approaches like co-simulations [6] are able to link different models, however, they are limited to quantitative, computer-based models, and the data handleable with them. Decision-making in the circular factory is further complicated by the fluctuating availability of data regarding distinct products and product generations. One cannot rely on the availability of such amounts of data, which are required by certain data-driven prediction methods. Similarly, the reprocessing of used products requires specific design knowledge about function-relevant design parameters and their interactions. This can be achieved by extensive explorative investigation of linear and circular products. The specific design knowledge needs to be considered in decision-making and applied at the product instance level.

There are several numerical and statistical models that address decision-making in production planning regarding disassembly and remanufacturing [7]. Despite accounting for the mentioned uncertainty, the models operate at a higher level and do not consider the product itself in detail as necessary for reprocessing in the circular factory. On the other hand, some models support sustainable product development, primarily through life cycle assessment, but neglect the control of reprocessing [8]. Consequently, no reliable information basis for decision-making in the circular factory is available as of right now. To make it worse, the product instances returning from the market have seen very different lives regarding application and runtime, so they are worn down individually. In this context, tolerance-focused methods exist [9] as well as first approaches targeting product functionality [10]. However, these approaches do not consider the wear of used products, as they are concerned with the scatter of parameters caused by linearly manufacturing new products. Notably, product components from different used products may be combined to remanufacture viable new products. Thus, the optimal material flow for components does not only depend on a single product instance, but on the whole set of available product instances and their components.

In summary, the problem is that a comprehensive data processing method to deal with the aforementioned requirements of the circular economy is missing. This leads to the research question of this paper:

How can product data be combined and processed to prepare informed decisions in the circular factory with the specific boundary condition of variable products returning from the market in unknown conditions?

2. Background on Functional Models in Circular Factories

2.1. Product Handling in the Circular Factory

At first a used product returns from the market and enters the circular factory. The precise product generation and variant are not known beforehand. Similarly, overall condition differs significantly, due to the individual wear of each product instance. For example, an angle grinder could have been used at a dusty construction site with medium loads and short working cycles or at a pressure vessel manufacturer, where it runs long working cycles under high loads but in a less aggressive environment. Depending on the exerted operation, different components are more or less likely to be affected by wear. This renders the requirement for thorough inspection and very versatile remanufacturing processes. Upon entering the circular factory, an initial function test of the returned product is a crucial first step. The product is considered as a complete unit in this first inspection and the degree of function fulfillment is measured. Latter can include qualitative characteristics such as a closed power connection from the electric motor to the tool and quantitative information such as vibration measurements.

With the initial inspection, a process of iterative disassembly and diagnosis of the used products and subsystems begins. In this process, each of the following steps depends on the findings and decisions of the current step. With a functional model, the degree of functional fulfillment is related to the function-relevant design parameters. For instance, if one single component has been found to compromise the entire product, the disassembly and measurement should focus on its specific subsystem. In most cases, however, multiple subsystems will be compromised and numerous operations are required. Additionally, the disassembled components of one system are not necessarily remanufactured to form a single new product. Instead, corresponding subsystems may be combined crosswise from different product instances to achieve higher degrees of function fulfillment.

The final decision on reprocessing and recombination is based on the fulfillment of the functional requirements. Therefore, the prediction of the degree of function fulfillment via the functional model is a major challenge within the circular factory. Diverse prediction approaches of different natures and requirements, both expert-driven and data-driven, are employed to enable the described decisions within the circular factory. The foundations of such prediction models regarding knowledge sources, products, and measurement data vary broadly. In our work, we focus on how the provided data, knowledge, and tools can be combined to achieve reliable predictions.

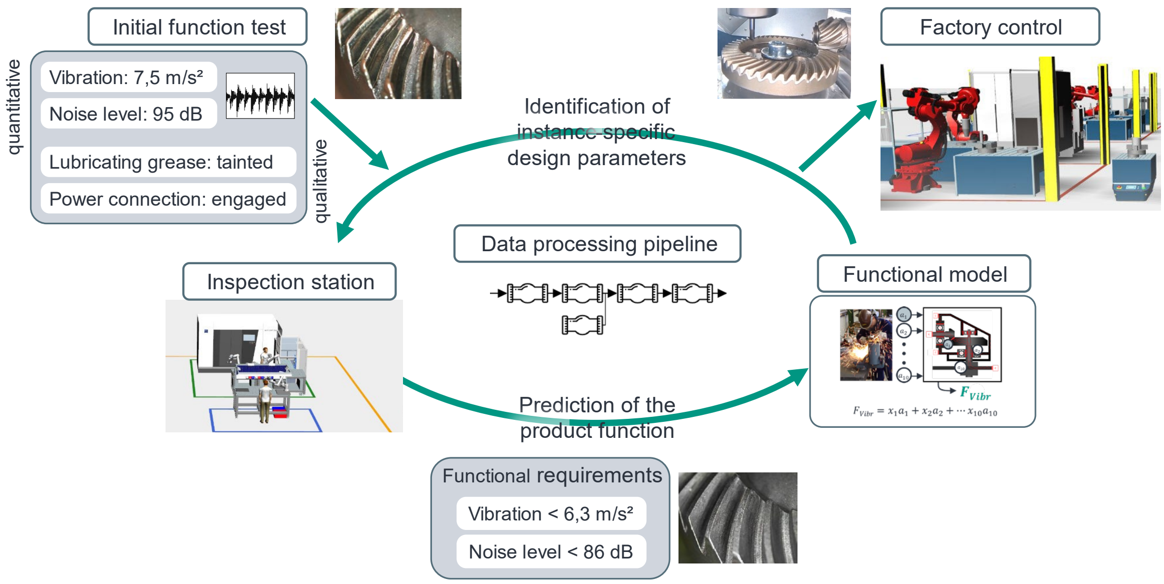

Figure 1: Illustration of the inspection and remanufacturing process in a circular factory for angle grinders. Contains graphics from KIT wbk/Fischmann.

2.2. Functional Model

As mentioned above, the circular factory makes use of a functional model to provide reliable information bases for disassembly and remanufacturing decisions. Consequently, it is necessary to identify the function-relevant design parameters and their relation to the product function. Regarding the angle grinder, the product function can be expressed through the vibration. A function model, in this case, maps the characteristics of the design parameters to the degree of function fulfillment. Thus, the model takes on two different roles in the circular factory. On the one hand, the degree of function fulfillment can be used to infer the characteristics of the function-relevant design parameters. This information is crucial for the iterative disassembly and diagnosis of used products at the beginning of the circular process. On the other hand, the functional model enables a prediction of the product function based on the characteristics of the design parameters. This allows different recombination variants of subsystems and components to be evaluated. By comparing the output with the functional requirements of the new product, the desired functionality can be theoretically ensured. Figure 1 illustrates the role of the functional model within the product handling process in the circular factory for angle grinders.

Regarding the actual structure of the functional model, different approaches can be used to perform the prediction task. Expert-driven models and data-driven models are particularly worth mentioning here. These approaches can either be used individually or in combination. The outline of their characteristics and examples will be shown in the following, emphasizing the importance of both model types.

Expert-Driven Models: Expert-driven models are manually constructed and tuned to contain external product knowledge, e.g., from conceptualization and testing. These models are white box models, in which physical facts, measurements, hypotheses and product knowledge may be modeled explicitly. As a result, they are formulated for a specific product generation and variant and their design requires manual effort and specific empirical product data.

The expert-driven approach of the functional model links qualitative and quantitative models by formulating design hypotheses [11]. Qualitative models are used to identify the function-relevant design parameters through the systematic analysis of the product. The Contact and Channel Approach [12] can be used to trace the chain of effects of individual design parameters in the system. The Design-Structure-Matrix according to [13] can provide information about the influence of the design parameters on the system behavior. This allows for the formulation of design hypotheses that link, for example, the geometry of the tooth flank of the bevel gear with the vibration of the angle grinder. Based on the design hypotheses, a targeted quantification of these design-function relationships is possible using empirical and analytical approaches. This process results in the creation of regression models for the relationship between the function-relevant design parameters and the degree of function fulfillment in a predefined parameter range.

Data-driven Models: The product data gathered during the operation of the circular factory facilitates the employment of purely data-driven approaches, as contrary to expert-driven approaches. Data-driven models rely exclusively on computational intelligence and machine learning methods to model physical systems using available data [14]. As the amount of historical instance-specific product data increases, predictions of machine learning and deep learning models are expected to grow more reliable. Thus, it is possible for data-driven approaches and black box models to enhance the expert-driven white box models or identify relations that are not accessible to the latter.

After the circular factory has been in operation for some time, the question arises of which approach of the functional model should be consulted, to obtain the most accurate predictions. Indeed, combinations of multiple predictions in a model ensemble may even further increase prediction accuracy and reliability.

3. Combining Expert- and Data-driven Models to Data Processing Pipelines

Depending on the circumstances, one should opt for a different model or even a combination of such. In this paper, we present a concept for the design of data processing pipelines for product data in a circular factory for angle grinders. As previously explained, multiple decisions regarding subsystem and component treatment have to be made for each product instance entering the circular factory. We propose the usage of data processing pipelines to exploit available product data, as well as existing models and data processing algorithms to produce predictions and thus support decision-making in the circular factory. In the scope of our work, we use the term data processing pipeline to describe a series of data-based operations targeted at predicting a specific condition or value.

Thereby, contrary to most problems in data science or automated machine learning (AutoML), the input data is not fixed beforehand. Instead, a pool of different data sources, from which one or multiple may be selected, is employed. This necessitates the availability of not only a syntactic but also a semantic description of these data. Furthermore, this requirement can be extended to algorithm descriptions analogously. As an essential step, the unified and comprehensive descriptions enable crucial decisions in automated pipeline construction, e.g., which algorithms and data are compatible, or which data can be used interchangeably.

In many AutoML approaches focusing on the automated selection of data processing models, the structure and grammar of the data processing pipelines are predefined and not easily customizable by the user [15]. This is not the case for the Open-Source solution CLS-Luigi, which is a use-case agnostic tool for the efficient optimization of fixed-input data processing pipelines [16]. CLS-Luigi enables the user to model a pipeline template and provide viable algorithm choices. Based on the template, CLS-Luigi exhaustively searches the algorithm pipeline yielding optimal results on the provided data. CLS-Luigi adapts the well-established synthesis framework, the combinatory logic synthesizer (CLS) [17], to automatically generate all pipeline variants based on this repository. CLS has already proven effective in many engineering applications such as design spaces of motion planning [18] and simulation models in warehousing and manufacturing [19].

The synthesized pipelines are implemented in Luigi, a popular Python library for building and executing data pipelines of batch jobs. Using Luigi pipelines is highly advantageous because it is agnostic to the type of computation; users can construct pipelines with algorithms from different fields, such as machine learning, combinatorial optimization, or physics. Moreover, Luigi caches intermediate pipeline outputs and avoids recomputing identical sub-pipelines with existing results [20].

CLS-Luigi offers a programming interface that closely resembles regular Luigi code, encapsulating type-theory and logic-related parts of CLS in a form that analytics experts can conveniently use. By applying combinatory logic, CLS efficiently synthesizes all feasible pipeline variants and returns a regular tree grammar that can be used to search the space resulting pipelines [17].

4. Conceptualization of Data Processing Pipelines in the Circular Factory

In the circular factory, various prediction tasks arise during the reprocessing of used products. This includes instance-specific error classifications during inspection and prediction of product function and reliability before reassembly. Figure 2 shows the build-up of different pipeline variants dealing with these tasks. Therefore, information from the product design phase is combined with information obtained during the runtime of the circular factory. While the product design is mainly expert-driven, the factory operation often relies on data-driven approaches. The individual components of the pipeline draw from the three central elements – models and algorithms, knowledge, and data.

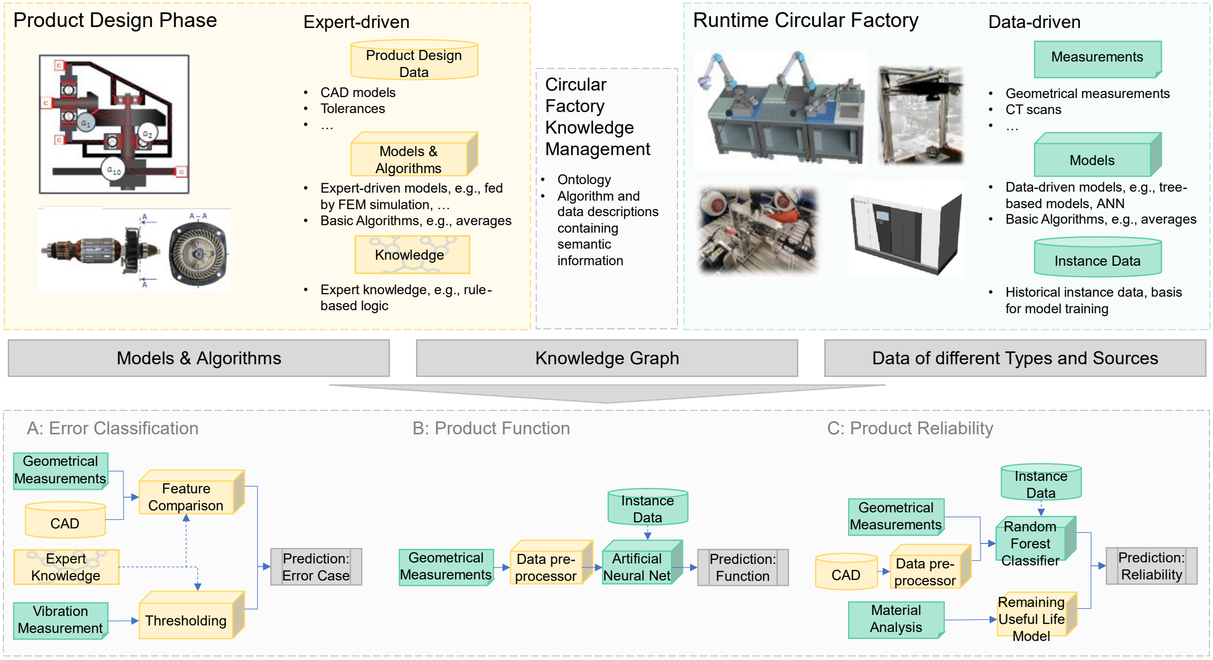

Figure 2: Build-up of data processing pipelines for various prediction tasks in the circular factory.

In the following, we present concrete application examples for data processing pipelines within the circular factory for angle grinders. These examples focus on the gearbox and map the two roles of the functional model mentioned above and shown in Figure 1. Subsequently, we carry out the actual construction of specific processing pipelines taking into account different data sources.

4.1. Application Examples

The first example addresses the initial inspection and disassembly of an angle grinder for which the data processing pipeline performs an error classification. In the second example the processing pipeline results in the vibration prediction to evaluate the reassembly of the gearbox.

Initial Inspection and Error Diagnosis: When used products return from the market to the circular factory, an initial functional test is carried out. The functional model then uses the data to identify relevant parameters for the inspection of the unique used product. A number of possible error cases exist, which must be identified. For example, the presence of specific frequency bands can indicate a broken tooth on the bevel gear. The used product is then disassembled and diagnosed in an iterative process that is always adapted to the current condition of the subsystems and their components. If there is no tooth breakage, the gear is geometrically measured to identify any damage to the tooths. Optical detection using laser scanning results in coarsely resolved point clouds, while the CT scan generates finely resolved 3D objects. Depending on the wear of the tooth flanks, a subsequent material characterization provides information about any crack formations.

Additional knowledge from the preceding product design process can be employed in the product inspection. For instance, the CAD model enables the identification of geometric deviations in the tooth flank due to wear. Furthermore, finite element calculations can be used to predict the structural integrity of the inspected tooth root under representative load profiles.

Based on the results, decisions regarding the disassembly and reprocessing of the gears are taken. For example, a bevel gear with a broken tooth is sorted out directly after disassembly. In this case, recycling of the bevel gear seems to be the right approach. Bevel gears with heavily worn tooth geometry can be remanufactured using subtractive-additive manufacturing processes, while gears with slight wear may only require reconditioning.

One rather simple and easy-to-understand prediction task, to which we aim to apply data processing pipelines, is the prediction of the specific error case „tooth pitting“ of the bevel gear. In this case, we expect data processing pipelines to output a numeric value indicating the presence of the error class, possibly combined with uncertainty information required for insightful decision-making in the circular factory.

Gearbox Assembly and Vibration Prediction: At the gearbox subsystem, the evaluation of different combinations of the bevel gear and bevel pinion before reassembly is of central importance. This requires the combination of the data and uncertainties of both components. In this case, a data processing pipeline targeting an output value indicating the vibration as the product function can be designed. Once again, the data processing pipeline is based on the same comprehensive descriptions of data, knowledge, and models and algorithms available in the circular factory. However, for this prediction task, the utilization of other data sources and algorithms will very likely be required to achieve high prediction accuracies. After prediction, the vibration values of the possible combinations are compared with each other and the functional requirement of the product. Concerning the recombination into a new product, the bevel pinion can, for example, come from another used angle grinder or be a linearly manufactured new part that exactly matches the defined specifications of the product at hand.

4.2. Data Processing Pipeline Examples

For the actual data processing pipeline, the first application example described in section 4.1, the prediction of the error case „tooth pitting“, will be considered. To communicate the idea of different viable data processing pipelines, we will outline three (manually constructed) data processing pipelines, which tackle the described prediction task. One is fully based on expert-driven models, the second is exclusively data-driven and the third shows a hybrid approach.

In an expert-driven process, the decisions are based on specific design knowledge that has to be gathered beforehand. This regards to the analysis of the frequency bands and the geometrical deviation of the tooth flanks from the CAD model. Figure 2 (A) depicts the described data processing pipeline. Data inputs are parameter measurements performed on the specific product instance: Vibration data and 3D surface measurement of the bevel gear. Additionally, the CAD model of the bevel gear, i.e., external knowledge from product design, is incorporated. A simple bandpass filter and thresholding are initially applied to the instance vibration data. Subsequently, if pitting is suspected, a deviation computation is performed to measure the divergence from the original product shape. If a sufficient deviation exists, the error is classified as „tooth pitting“. This data processing pipeline operates purely on product knowledge, models from the design phase and instance measurement data – no historical data about the product is required.

In contrast to the previously described data processing pipeline, two pipeline versions that incorporate data-driven approaches and employ historic product measurement data were manually constructed. Figure 2 (B) and (C) illustrate these pipeline examples. In version (B) a pipeline relying exclusively on data-driven algorithms is illustrated. This data processing pipeline utilizes instance measurement data and historic instance data. Employing the historical data, a learning-based algorithm is fitted to predict the presence of pitting based on vibration and noise level measurements. This pipeline example classifies without requiring the conduction of costly 3D measurements. Version (C) in Figure 2 illustrates a hybrid pipeline employing both expert-driven and data-driven methods. The pipeline is very similar to the first version (A), but instead of comparing 3D surface measurements to CAD data and using an expert-driven prediction method, a data-driven approach is used to predict the error „tooth pitting“ based on vibration and 3D surface measurements. Again, historic instance measurement data is utilized as training data for the black box prediction model.

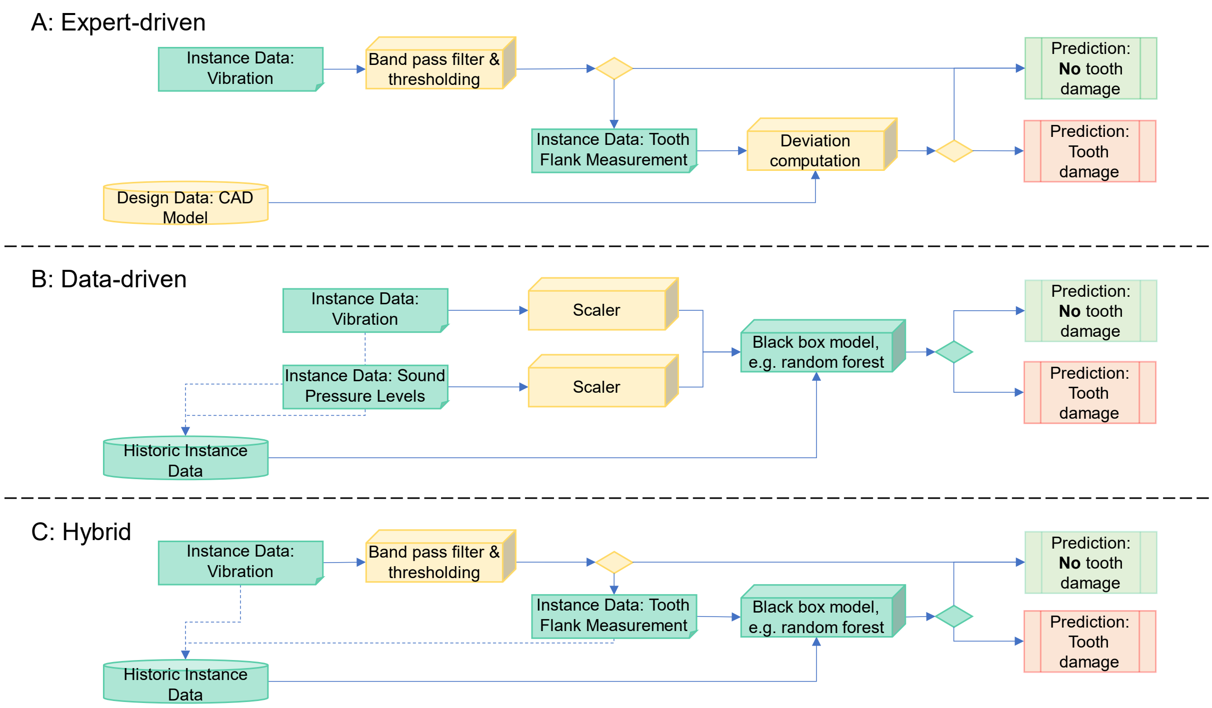

Figure 3: Exemplary data processing pipelines for the diagnosis of the error case "tooth pitting ".

As explained above, we do not limit the input data of the corresponding prediction pipeline to a specific set of data, e.g., to the vibration data measured during the initial inspection, or to the product instance measurement data in general. Instead, we allow, and intend, a synthesized data processing pipeline to feed on any available data, which it renders beneficial for the prediction task. Summarizing the above, three completely different data processing pipelines with identical prediction objectives were introduced. At the same time, they all might be viable choices to predict the presence of the error case „tooth pitting“ for a given product instance.

5. Discussion

The presented data processing pipelines show a conceptual answer to the research question “How can product data be combined and processed to prepare informed decisions in the circular factory with the specific boundary condition of variable products returning from the market in unknown conditions?” They are manually constructed examples for illustration of the concepts and modeling abilities of data processing pipelines. Furthermore, the advantages of CLS-Luigi over many other AutoML approaches regarding the structure and grammar of data processing models are highlighted. However, as we aim to tackle numerous prediction tasks within the circular factory with such pipelines, their manual construction is not feasible. The pipeline synthesis tool CLS-Luigi does not yet capacitate the work with multiple data sets or incorporate semantic information. We intend to exploit the exceptional pipeline synthesis capabilities of CLS-Luigi and to enhance it to construct data processing pipelines consistent with the needs within the circular factory.

To achieve this objective the systematic cataloging of all potential data sources and data processing algorithms, including structural and semantic information, is required. In this systematic description, especially information on the interpretability of the data needs to be contained. The assignment to either the product or product instance and the interchangeability of data should be highlighted. Similarly, algorithm descriptions must contain analogous information on the operational level and its corresponding input and output. We aim to encapsulate the relevant semantic data and algorithm information in a joint concise ontology.

This ontology can then be used to determine the compatibility of data sources and algorithms, e.g., to decide whether a given algorithm may use a specific data source as input, or whether two different algorithms can be applied consecutively.

To select the best possible pipeline version, some means of evaluating specific pipeline compositions are necessary. This, yet again, requires either the presence of adequate data within the circular factory, or human assistance. In our vision for the implementation of data processing pipeline synthesis, human assistance is requested in the early stages of factory operation, when no adequate evaluation data can be extracted. In later stages, evaluation data in the form of instance-prediction pairs are available. Equally appealing, we aim to investigate transfer learning approaches to adopt pipeline construction results from earlier products to new product generations.

The biggest limitation of the presented work is, in our opinion, its early stage of conceptualization and the lack of quantitative experimental results. An adequate data basis is highly complex and not readily available, but required to perform the necessary experiments and evaluations. We will address this issue in future research. A more fundamental limitation of the concept is caused by the high requirements regarding data and algorithm description. In a complex system like the circular factory, where numerous data sources and types are to be expected and many different models and algorithms are prospectively applicable, the effort of constructing a concise information ontology is associated with great effort.

6. Conclusion and Outlook

In this paper, we presented problems and challenges relevant to the implementation of a circular factory that reprocesses used products in order to return them to the market. Within such a process, which includes product disassembly, inspection, reprocessing and assembly, a large number of interdependent decisions need to be taken. An adequate data basis for such decisions is not readily available. While numerous different data sources are applicable, the amount of available data fluctuates and problems regarding data formats, compatibility and interpretability exist. We propose the implementation and application of synthesized and optimized data processing pipelines to provide adequate decision support. The operational processes within the circular factory were analyzed, highlighting exemplary applications for the advantageous use of data processing pipelines. We presented manually constructed data processing pipelines to fulfill the corresponding prediction tasks, taking into account different data sources and algorithms. Lastly, the requirements for enabling automated data processing pipeline construction were outlined, based on a concise information ontology containing structural and semantic information on all available data sources, data processing methods, and algorithms

In future work, we intend to construct an exemplary information ontology representing relevant parts of the circular factory's processes. Based on this ontology and the open-source tool CLS-Luigi, we will implement a solution for automated pipeline synthesis in the context of the circular factory for angle grinders. For a few relevant examples within this environment, we will examine and evaluate the automatically synthesized algorithm pipelines. Another interesting direction for future research is the formulation of a procedure model for the implementation of automated data processing pipelines throughout the circular factory, based on the pipeline synthesis results for selected application examples.

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