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Digitalized manufacturing process sequences – foundations and analysis of the economic and ecological potential

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ABSTRACT

As a consequence of the increasing digitalization of production, the availability of data from individual manufacturing processes and components is rising continuously. Digitalization affects various levels of production, such as the design of manufacturing processes, technology planning, quality monitoring, or logistics control. The contribution of this paper is to present the foundations for digitalized manufacturing process sequences and to develop data-based models and methods for the design of economically and ecologically optimized process sequences. For this purpose, a procedure for cross-process life cycle assessment was developed and carried out in order to evaluate the various ecological effects resulting from manufacturing and, in particular, different process designs. This ecological evaluation was combined with the evaluation of economic efficiency in order to provide an integrated evaluation as the basis for the design of manufacturing process sequences. In addition, the effects of the individual manufacturing process designs or process parameters on component quality were analyzed and an approach was derived for determining cross-process dependencies. The basis for these developments is a process sequence for the manufacture of pinion shafts used in electric car gearboxes. This digitalized process sequence consists of the processes soft cutting, gear hobbing, case-hardening, cylindrical grinding, and gear grinding, and over 100 components were manufactured with various process designs. This enabled an extensive amount of process and quality data to be collected throughout the process sequence. The application of the developed methods to the aforementioned process sequence underlines the high potential for the optimization of the target parameters quality, economy and ecology through cross-process analyses of digitalized manufacturing process sequences. Finally, an outlook on further developments regarding the digitalization of manufacturing process sequences is given.

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Introduction

In the face of increasing global competition, the economical and ecologically sustainable as well as efficient manufacture of products becomes a prerequisite for manufacturing companies aiming to secure their competitive position in the long term. The isolated improvement of the individual processes does not necessarily lead to the optimal manufacturing process sequence, since dependencies regarding economic efficiency, ecology, and quality between processes are not taken into account [1,2]. Therefore, the holistic optimization of the entire process sequence is crucial for a manufacturing company in order to remain sustainably competitive [3]. Here, a significant potential lies in the data-based examination of the dependencies of manufacturing processes in a sequence. In order to evaluate these dependencies on the basis of data and to derive optimizations, new methods must be designed and continuously developed.

The results of this research enable a complete evaluation and optimization of manufacturing process sequences in parallel with

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regard to economics, ecology and quality as well as the analysis of dependencies between individual manufacturing processes on the basis of digitalized manufacturing processes and data-based approaches. In this context, this is the first time that data-based approaches make it possible to detail the scope of investigation down to individual manufacturing process parameters with their effects on subsequent manufacturing processes, and the overall target for the entire process sequence.

Approaches for the digitalization of manufacturing processes and process sequences as well as for the design of economically and ecologically optimized manufacturing process sequences taking into account the component quality are analyzed in section on the state-of-the-art. In the following section on preliminary work, the experiments and collected data, which are the basis for the subsequent developments, are described. The findings obtained in this interdisciplinary research as well as the developed approaches are presented in the section on findings and developments. A summary and an outlook regarding digitalization of manufacturing process sequences and subsequent development steps is given in the last section.

State-of-the-art

There is a large number of research approaches that describe the potential of digitalization for manufacturing. Therefore, the approaches presented in this section are structured according to their level of detail in production, starting first with the superordinate perspective of production systems. The level of detail is then continuously increased, from manufacturing systems to manufacturing process sequences, technology chains, and to individual manufacturing processes.

Monostori describes Cyber-Physical Production Systems (CPPS) as a system of autonomous and cooperating elements and subsystems that connect with each other situationally across all levels of production [4]. Meissner and Aurich describe the advantages that CPPS can offer in the long-term for process planning and scheduling. In particular, the real-time data resulting from networked machines and components in combination with a planning system enables improved scheduling, since unscheduled events or delays can be analyzed and considered in a targeted manner [5]. Monostori et al. derive the potentials and future challenges of CPPS. The authors explain that the use of cyber-physical production systems and the networking of manufacturing processes will offer significant advantages for all levels of production [6]. As Pennekamp et al. describe in their approach, the digital infrastructure is a prerequisite for the implementation of corresponding concepts to improve quality, economics and ecology (e.g. through data-based real-time wear or quality measurements) within the framework of the internet of production. The authors describe the need to be able to control manufacturing processes in real time, to process and store the emerging heterogeneous data, as well as to meet data security requirements, and derive a concept for a possible infrastructure [7]. The approaches presented, as well as many others, describe the high economic and ecological potential that results from digitalized production systems, whereby the focus in each case is on higher-level models or frameworks [8,9].

In addition to the previously analyzed approaches, there are various approaches for the design and optimization of manufacturing systems and manufacturing sequences (as a sequence of directly value-adding manufacturing means extended by all non-directly value-adding steps, such as transport), on the basis of digitalized systems [10]. In this context, Serrano-Ruiz et al. analyzed 68 approaches to smart manufacturing scheduling. The authors concluded that the application of methods from digitalization or the generation of digital twins for a component or machine has a high potential for the scheduling of manufacturing sequences and for production planning. In this context, many of the approaches studied include frameworks for applying appropriate methods to support scheduling in production. The individual manufacturing processes are assumed to be fixed with regard to the process parameters [11]. This fixation of process parameters or the view of manufacturing processes as a black box (no manufacturing-technological consideration of the processes) is also evident in other approaches to scheduling [12–14]. The same applies to other promising approaches in the field of designing and optimizing manufacturing systems and sequences e.g. for bottleneck prediction [15], for determining optimized lot sizes [16], for capacity-optimized planning in general [17], and for optimizing order sizes [18].

Zhang et al. take up the aspect of considering manufacturing processes as a black box and describe that the adjustment of process parameters has a high influence on the economic efficiency regarding the manufacturing of components. Therefore, they developed an approach in which they set the production speed as an adjustable process variable [19]. A corresponding concept was taken up in later approaches [20,21]. The effects of adjustments of process variables on component quality, as well as technological dependencies between manufacturing processes are not the focus of these approaches. As Denkena et al. and Wuest et al. showed in their approaches, these technological dependencies must be taken into account within manufacturing process sequences (as a sequence of directly value-adding and resource-related manufacturing processes [22]) in order to achieve a qualitative and economical optimum [23,24]. Therefore, Wuest et al. developed a description model to represent the manufacturing history with qualitative technological dependencies [24]. Stavropoulos et al. developed a framework to optimize sequenced additive and subtractive processes in order to improve the component quality as well as economic and ecologic KPIs. To predict process values as well as component quality, the authors combined simulations and models of two processes [25]. The combined planning of additive and subtractive processes is also part of further approaches [26]. Another approach that enables the adjustment of process parameters for quality prediction was developed by Hejazi et al. The aim of this approach is the cross-process optimization of multi-stage manufacturing processes (manufacturing process sequences). Here, the individual processes are mapped via response surface models and linked on the basis of defined intermediate states. Methods for the determination of the models as well as for the identification of interfaces are not presented, since the focus is on optimization and not modeling [27]. This also applies to comparable approaches [2,28]. In addition, economic or ecological target criteria are insufficiently considered by these approaches.

Besides the approaches for designing manufacturing process sequences, there are a large number of approaches for data-based planning and optimization focusing on individual manufacturing processes. For example, Arun et al. used acoustic emissions to monitor grinding wheel conditions [29]. Gauder et al. used a deep learning approach to detect pores in milling processes in-line [30]. Other approaches use data-based methods to evaluate the current wear condition and the expected service life [31,32]. Gajate et al. provide another example using neuro-fuzzy techniques for wear monitoring in turning processes [33]. Digitalization thus makes it possible to determine optimized tool changes or dressing times, e.g. via neural networks [34]. Radetzky et al. present various data-based algorithms from machine learning to design individual processes [35] and predict process outputs [35,36]. All these approaches, which are based on digitalized manufacturing processes, relate to one process each.

As described in the introduction, it is relevant to consider not only component quality but also the economic and ecological

efficiency of manufacturing. For example, Shi et al. present an approach to integrated environmental and cost assessment based on life cycle assessment and life cycle costs for mechanical product manufacturing [37]. Grünebaum combines material flow costing with life cycle assessment for the integrated evaluation of process sequences, where the weighted ratio of the target criteria is determined by a factor to be defined by the user [38]. In order to combine different target criteria, Saaty developed the analytic hierarchy process within which criteria are weighted and combined to a target value [39]. To simplify the application, Goepel implemented the analytic hierarchy process in an online software tool [40]. In addition to Saaty's generic approach, special methods exist for the integrated assessment of economic and ecological target variables. In the review by Pizzol et al., different monetary weighting methods are compared [41]. Although various approaches explain the need for an integrated ecological and economic assessment, it is deduced that the methods used are based on high uncertainties as well as partly subjective assessments [41–43].

Findings and developments

As analyzed in the previous section, there are various approaches to optimizing digitalized manufacturing processes/process sequences. However, these either describe an overarching framework and the fundamental potentials of digitalized production, or focus on individual processes. The higher-level approaches lack the manufacturing technology detail, e.g. with regard to the consideration of process parameters or dependencies between manufacturing processes throughout the process sequence. This contrasts with process-focused approaches that do not consider cross-process dependencies. Transferable methods as well as the parallel economic and ecological evaluation remain insufficiently explained.

In order to evaluate the economic and ecological potential of digitalized manufacturing processes in an industry-relevant use case as well as in a scientific environment, to develop innovative data-based methods, and to discuss the resulting scientific questions, over one hundred pinion shafts that are used in electric vehicle gearboxes were manufactured in a fully digitalized process sequence. In order to achieve innovative and future-oriented results and be able to use the data collected across all disciplines, various experts from the individual manufacturing technologies and from the fields of digital transformation, technology management and process control were involved.

In the following, the implementations and findings on digitalized manufacturing process sequences are presented (see Fig. 1). First, the process sequence and the underlying experimental design are introduced in the Data generation section Subsequently, the area of data management which provides a basis for the targeted and sustainable use of the collected data is introduced. In this part of the paper, the data preprocessing as well as storage and sharing are presented.

Subsequently, the developed approaches for data usage are described. As explained above, the design of manufacturing process sequences optimized for economics and ecology requires an understanding of existing dependencies in the process sequence. The following section therefore explains the fundamentals of cross-process dependencies and an approach based on stochastic modeling to determine them. In order to evaluate the process sequence on the basis of ecological criteria, a developed approach to life cycle assessment (LCA) in manufacturing and the application of the approach to the manufacture of pinion shafts are explained. Subsequently, the LCA will be linked to an ecological efficiency assessment approach to provide an integrated assessment and optimization. In addition, the authors will explain what potential the digitalization of manufacturing process sequences has for optimizing individual processes. The example of the grinding process is used to explain how data from the previous process can contribute to the optimization of grinding.

Data generation

As a use case, a pinion shaft for gearboxes of electric vehicles with various geometric features was selected, see Fig. 2. Of particular relevance to the functionality of the shaft are the two bearing seats (features F09 and F41), the shoulder for the shaft-hub connection (feature F04) and the teeth of the gear (features F14 to F37). A total of 104 shafts were produced and all manufacturing processes (except the hardening process) and all quality measurements were carried out internally. This allowed for consistent and uniform data acquisition and assignment of the laser-marked components. In addition to machine data and quality measurements, the database was expanded with data from additionally installed sensors. Furthermore, the boundary conditions of the production were recorded and documented.

The manufacturing process sequence is as follows: soft machining (turning, milling and drilling) on the DMG MORI NZX 1500 machining center, followed by gear hobbing on a Liebherr LC180. The component hardening was performed externally as a batch, whereby the process parameters and other boundary conditions were kept constant for all shafts. Subsequently, cylindrical grinding processes were performed on a Studer S41 followed by gear grinding on a Klingelnberg Viper 500 KW. Various quality variables (component characteristics) were measured after each manufacturing step (see Fig. 2). A Klingelnberg P65 measuring machine was used for the automated measurement of macro-geometric quantities such as diameter or concentricity and the gear quality. A tactile measuring device from Jenoptik was used to determine microgeometric characteristics (roughness values) on the heels. Furthermore, supplementary measurements, e.g. to determine tool wear, were carried out in the machines (in-line) e.g. by using camera systems [44].

A targeted experimental design was used to evaluate the economic and ecological potential offered by the digitalization of

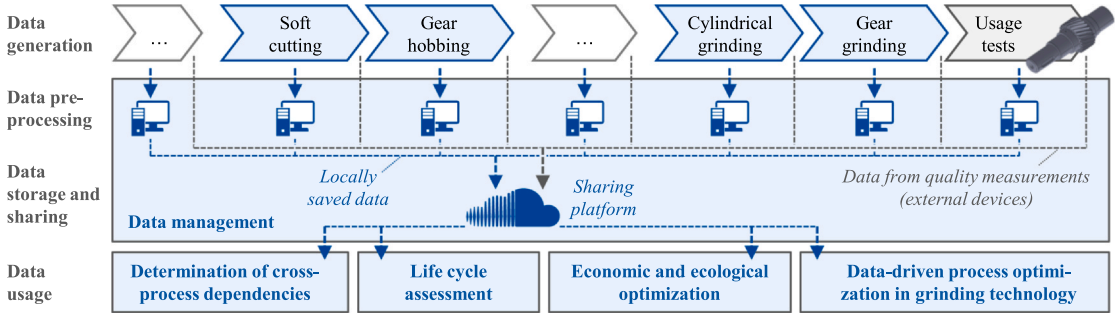


Fig. 1. Overview of the developments on digitalized manufacturing process sequences in this paper.

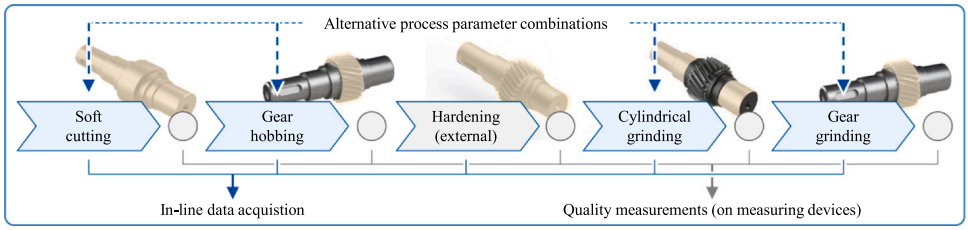


Fig. 2. Manufacturing process sequence for pinion shafts.

manufacturing process sequences. After various set-up tests to stabilize the processes (not included in the experimental design), 30 components were manufactured with a reference parameter set. Here, all process parameters and other boundary conditions were kept as constant as possible, which was e.g. achieved by regularly exchanging tools and dressing processes for each component. In so-called experimental groups (EGs), the process parameters were varied and thus alternative, presumably more productive parameter sets were investigated. For example, in soft cutting, the feed rate and/or the cutting speed was increased, the finishing process was omitted or worn tools were used. The processes' designs were varied in coordination with each process in such a way that the effects of the parameter change but also cross-process effects due to the influence of processes on each other can be investigated. The entire experimental plan (reference group and 15 EGs) is shown in Table 1. Each experimental group contains five components, as past projects have shown, this number is sufficient for the determination and comparative evaluation of economic and ecological target values, which is also confirmed by the results.

Data management

By using an individual component ID, all data was assigned to the individual laser-marked shaft. This allowed the unambiguous

Table 1
Experimental design and experimental groups.

Experimental group *(EG)*	Soft cutting *Roughing and finishing*	Gear hobbing	Cylindrical grinding *Roughing an finishing*	Gear grinding	Number of components
EG00	Reference (-)				31
EG01	-	-	No dressing	Feed rate ↑	5
EG02	-	-	No dressing & Feed rate ↑	Feed rate ↑↑	5
EG03	-	No finishing	Feed rate ↑	-	5
EG04	-	Cutting speed ↑	Coverage dressing ↓	-	5
EG05	Experimental group for residual stress analysis (See EG00 – no grinding processes)				4
EG06	Feed Rate ↑	-	No dressing	-	5
EG07	Feed Rate ↑ & Cutting speed ↑	-	No dressing & Feed rate ↑	-	5
EG08	Worn tool	-	-	-	5
EG09	Worn tool	No finishing	Feed rate ↑	-	5
EG10	Worn tool	Cutting speed ↑	Coverage dressing ↓	-	5
EG11	No finishing	-	-	-	5
EG12	No finishing	No finishing	Feed rate ↑	-	5
EG13	No finishing	Cutting speed ↑	Coverage dressing ↓	-	5
EG14	Experimental group for residual stress analysis (See EG11 - no grinding processes)				3
EG15	No finishing & Feed Rate ↑ & Cutting speed ↑	Wet processing	Feed Rate ↑	-	6

Soft cutting:
Feed rates (roughing): 0.2 mm/Turn, 0.3 mm/Turn
Feed rates (finishing): 0.12 mm/Turn, 0.2 mm/Turn
Cutting speeds (roughing): 250 m/min, 300 m/min
Cutting speeds (finishing): 300 m/min, 350 m/min

Gear hobbing:
Cutting speeds (first cut): 150 m/min, 200 m/min
Cutting speeds (second cut): 200 m/min, 250 m/min
EG00-EG14: Dry processing

Cylindrical grinding:
Feed rates (roughing Feature 04): 1.15 mm/Turn, 1.72 mm/Turn
Feed rates (roughing Feature 09 and 41): 0.96 mm/Turn, 1.44 mm/Turn
Feed rates (finishing Feature 04): 0.38 mm/Turn, 0.57 mm/Turn
Feed rates (finishing Feature 09 and 41): 0.32 mm/Turn, 0.48 mm/Turn
Dressing overlap ratio: 15, 10
Dressing cycles: one per feature (three per component), one per component

Gear grinding: Feed rate (finishing - constant): 1200 mm/min
Feed rates (roughing): 2000 mm/min, 2500 mm/min, 3200 mm/min

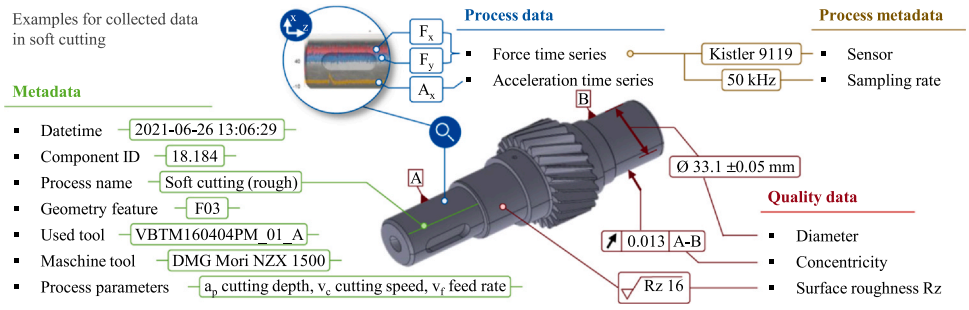


Fig. 3. Examples of metadata, process data, process metadata and quality data for the soft cutting process in the production of the pinion shaft.

assignment of data from different processes and sources to this component and thus was a prerequisite for the subsequent analyses.

The resulting data set along the manufacturing process sequence is divided into three main categories – metadata, process data and quality data – and one subcategory (process meta data). Examples of data for the soft cutting process are shown in Fig. 3. Metadata describes the higher-level fixed characteristics of a component (e.g. material), of the processes (e.g. process parameters), and of the machine tool used. Metadata can remain unchanged (like the component ID) for the entire process sequence, but can also change depending on the progress made in machining the component. Metadata is therefore diverse and the technology-specific metadata creates the challenge of defining a uniform semantic across all processes. Its generation succeeds via a previously elaborated experimental plan and process designs.

In contrast to metadata, process data that changes within a process step and can be precisely determined using metadata was recorded by internal and additional sensors (e.g. a force measurement platform for the times series of force curves during machining a component). With regard to the process data, the aforementioned subcategory of process metadata was introduced, which contains detailed descriptions of the origin of the process data. This includes the specification of the sensor technology used and the associated specific sensor information such as the sampling rate of the sensor. The last category is quality data, such as measured diameters or the surface quality of a manufactured shaft. For all processes, the collected data were classified into the described types. This created the highest possible comparability across the data and ensured that metadata in particular was available for subsequent analyses.

Sustainable data use becomes possible by storing all the data in one database/platform and describing it in detail, as well as assigning metadata (the procedure is described below). This enables data to be further analyzed for different applications as well as for the data set to be continuously extended. Automated linking is required in order to be able to correctly assign such amounts of data. For this purpose, a database was provided that could be accessed by every machine tool in the process sequence. This database contains the categories and characteristics of the metadata based on the experimental plan. Using National Instruments LabVIEW, the metadata and process metadata for the current process step were bundled and locally stored in a Technical Data Management Streaming file (TDMS) on the experimental computer. Each TDMS file contained the records of all associated data types of a single process step and is read from the metadata database/platform. Fig. 4 shows the links between the manufacturing process and the database/platform for soft machining on the DMG MORI NZX 1500 machine tool as an example. In addition to the process forces recorded via the Kistler 9119 and the accelerations recorded via the acceleration sensor PCB-356A15 on the tool, machine-internal signals such as the position, the speed, and the acceleration of the spindle were recorded. In order to be able to use the time series of the machine-internal signals and the different sensors (e.g. force, acceleration and energy sensors), additional time series channels with trigger signals were introduced via the machine control. These allow the time series of the individual sources to be synchronized with each other.

This approach was used for all machine tools in the pinion shaft process sequence. All data of the manufacturing process sequence are therefore collected on the sharing platform and used for cross-process analyses. While the machine-internal data as well as the sensor data are individual for each process, since they depend on the respective technology and machine, a uniform measurement was important for the quality data. Since the quality data are compared with each other after different processes of the process sequence, the measurements were all carried out on the same separate measuring machine.

Now that the implementation of data management has been described, it will be examined to what extent the approach used fulfills the FAIR principles and where there are further challenges or need for development. The FAIR principles (findable, accessible, interoperable and reusable) provide the basis for data management in the executed, interdisciplinary research [45] (see Fig. 5). These principles were developed on the premise that humans increasingly rely on support from machines to handle data at scale. Thus, the principle of findability emphasizes that humans, but also machines, must be able to find data in order to (re)use it. For the previously described manufacturing process sequence data, metadata as well as other data, must be assigned unique and persistent identifiers (principle F1). Currently, the recorded data is uniquely identified via a component ID. Process metadata and metadata provide information for humans and machines alike to find the acquired data for

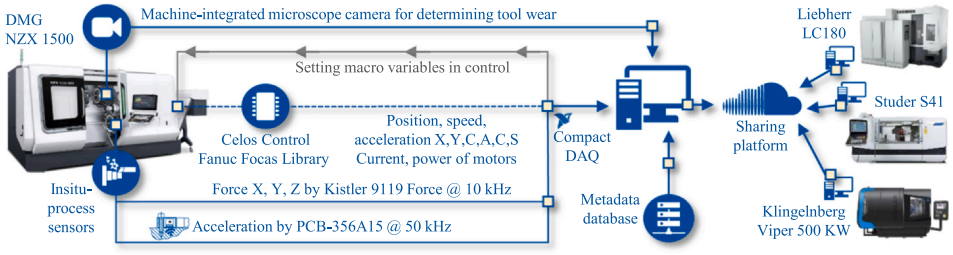


Fig. 4. Collecting and networking data obtained while soft-machining the pinion shaft.

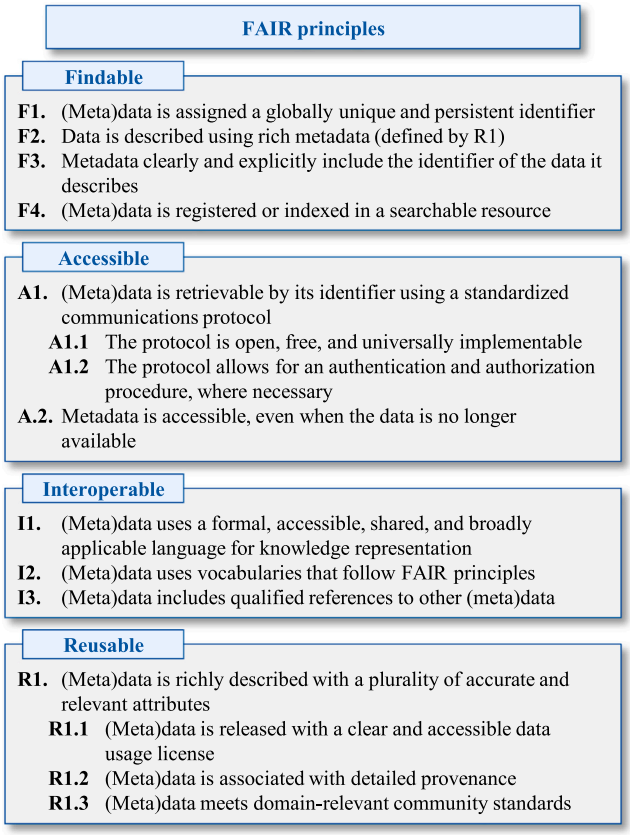


Fig. 5. FAIR data principles by Wilkinson et al. [45].

future research purposes and applications (principle F2). The metadata is linked to corresponding data (principle F3) within TDMS files. For the (meta)data to be findable, it must also be published on a data management (sharing) platform (principle F4).

For the purpose of data accessibility, future development steps will ensure that lab members can retrieve data via standardized and well-established communication protocols, e.g. HTTP or FTP (principle A1.1). Over the course of developing this data access point, authentication mechanisms will also be considered to restrict user rights (principle A1.2). At the current stage, there are no considerations regarding the dissolution of the recorded data (principle A2).

As explained above, data is saved in the single file format TDMS. This prevents interoperability issues originating from heterogeneous file formats (principle I1). However, in the long term, alternative/additional data formats are planned that will incorporate semantic technologies into the data management, which enable machines to understand contextual information and automatically reason over data (principle I2). Moreover, meaningful cross-references between data are required, e.g. from different processes. Currently, data from different points along the process sequence is linked by a component ID. Additional, cross-process contextual links facilitate automated processing of the data as well as future analyses performed by humans (principle I3).

Metadata, not only contributes to the findability of relevant data, but also makes it possible to assess whether the data is useful for new applications in the future (principle R1). Usage licenses for the generated data as well as data provenance are currently a minor concern (principles R1.1 and R1.2). All (meta)data is saved in a coherent format (TDMS), which can be analyzed using LabView, but also Python, a well-established data analysis language (principle R1.3).

Despite the data management measures taken, the contextualization of data from different manufacturing processes remains a challenge, which requires semantic enrichment of data to enable and facilitate diverse applications. Kalayci et al. report that data integration can consume significantly more time than the data analysis itself, while also being prone to errors, as the integration is done ad-hoc and manually. Therefore, they connect manufacturing data to an ontology with the aim of enabling data integration based on semantics, specifically for component quality analysis tasks [46]. Ontologies provide a vocabulary to model domain knowledge and contextual information [47]. By formalizing domain knowledge in an explicit way, they enable machines (and humans) to reason about the data. A wide range of ontologies have been proposed specifically for manufacturing with different objectives and application areas in mind [48]. The database presented in this paper will be used for multiple applications and therefore provides a case study to develop and evaluate semantic technologies such as ontologies from the combined perspective of the aforementioned use cases.

Determination of cross-process dependencies

As explained above, a manufacturing process sequence consists of all manufacturing processes that directly add value and contribute to the production of the final component. Each manufacturing process has an influence on at least one component state characteristic after the corresponding process [49]. In addition to the process itself (or the process design/parameters), the component characteristics before the corresponding process can have an influence on the process output (component state). In this context, component characteristics are understood to be, for example, the macro and micro geometry as well as the mechanical attributes of the near-surface zone [50]. The intermediate component states representing the transfer variables between the individual processes and therefore indicate the cross-process dependencies between processes, which are contained in the manufacturing history of a component (see Fig. 6) [24].

If the process parameters of a manufacturing process are adjusted, for example for the purpose of ecological or economic optimization, the effects on subsequent processes and the balance of the entire process sequence must always be taken into account [49]. These dependencies can also exist within a process, as some processes themselves are a sequence of sub-processes (like grinding consists of roughing and finishing).

Variations in component characteristics (as the output of a process) and permissible tolerances cause the input variables for subsequent processes to vary. This leads to the fact that the tolerances of the intermediate component states can also only be cross-process

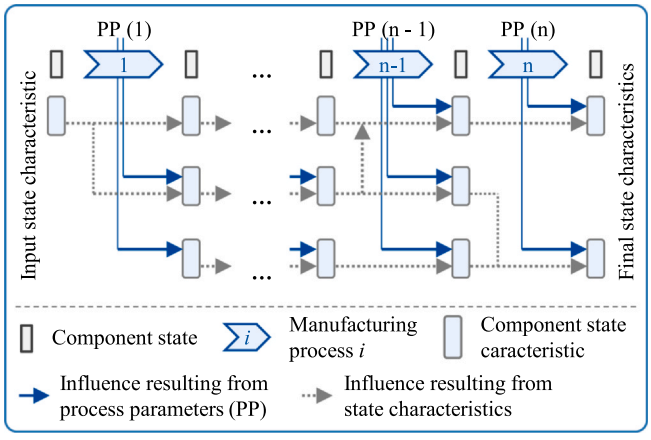


Fig. 6. Dependencies in manufacturing process sequences.

designed. One must take into account that only the final component characteristics (the final quality), which directly influence the functionality of the component, are relevant for customers. However, industrial applications often look different. Requirements for intermediate component states and tolerances are often estimated based on experience. Effects due to process adjustments on subsequent processes are often only considered when problems arise in the process sequence.

In order to search for possible dependencies between manufacturing processes or their sub-processes, a stochastic model is required that appropriately represents each process and aspects of their dependency. It must also be possible to fit the model to actual data in order to identify dependencies and test hypotheses regarding them. An approach is to derive a graphical model for the manufacturing process sequence under consideration. Graphical models are a promising concept for describing complex distributions and analyzing their structure, in particular as the basis for causal inference [51,52].

First, a set of symbols and variables is introduced that represents the processes and different types of data. In the second step, the identification problem will be formulated in stochastic terms. The restrictions as well as the model assumptions that are required in order to make the identification problem feasible will also be stated. The methodological approach is then discussed briefly and further model assumptions are derived. A procedure that results in a graphical model is described after all. This graphical model represents the dependencies between all processes. This section ends with a discussion on the reliability of the resulting model, the steps required for further validation, and the next steps for the data analysis using the graphical model.

For the data-based analysis of these dependencies, a representation of each (sub-)process is considered (e.g. the sensor time series from which appropriate, technology-specific features are selected). An example of sub-processes is the separation of soft cutting into roughing and finishing. The experimental groups with their individual parameter designs are represented by dummy variables indicating the allocation of each component to the parameter specification. The process sequence is divided into sub-sequences. A denotes the first sub-sequence of soft cutting roughing (i), soft cutting finishing (ii), cylindrical grinding roughing (iii), cylindrical grinding finishing (iv) and cylindrical grinding spark-out (v); B denotes the second sub-sequence containing the manufacturing of the gear features. Additionally, variables are distinguished by quality values (q), time series features of machine-internal or additional sensors that represent the (sub-)process (t) and the dummy variables indicating the process design as well as further meta data (p). Using these symbols as indicators, X_{ij}^{ab}, $i = 1, \ldots d_{abj} \in \mathbb{N}$, denotes a random variable that represents a process property of type $a \in \{q, t, p\} =: Q$ for sub-process $j \in \{1,\ldots,5\} =: H^A$ if $b = A$ (and $j \in \{1,\ldots,6\} =: H^B$ if $b = B$), where d_{abj} denotes the number of process properties (e.g. a time series feature) of type a for sub-process j in sub-sequence b (see Fig. 7).

In order to obtain a precise model of cross-process dependencies, stochastic relationships between variables representing different process-steps must be investigated. Stochastic dependencies between some variables can manifest themselves in various ways, e.g. in terms of the expectation or variance of one variable conditioned according to values of the other variables, but also the skew and further characteristics of the conditional distribution can be dependent. Due to the contrast of a comparatively small number of manufactured components and the possible dependencies of the several hundred candidate variables to be considered, the analyzed identification problem is considered high dimensional and poses a challenge when identifying the dependencies. However, this challenge is of high industrial relevance as manufacturing companies cannot run extensive experiments for parameter optimization in a planned or an existing serial production line and are incentivized to reduce experimental effort. This entails focusing on a practical compromise that is obtained by solving a feasible problem with strong model assumptions that still enable the identification of important dependencies.

The focus is therefore on identifying conditional mean dependencies, i.e. identifying the set of variables of multiple processes that a conditional expectation of a variable in a later process is dependent on, while the conditional expectation of that variable is independent on all other variables of the earlier steps. Here, the goal is to identify the smallest set of variables (in the sense of the number of elements) M_{ijab} under given conditions (A), (B), and (C) (see Fig. 7). Here one can see that a variable X in step $j \geq 3$ can still be dependent on a variable $Y_1 \notin M_{ijab}$ in step $j' \leq j-2$ because there can be a variable Y_2 in a step $j'' \in \{j'+1, \ldots, j-1\}$ that is dependent on Y_1 and X. Considering the factorization (cf. Fig. 7) for ordering $Y_1, \ldots, Y_k$ of all elements in $M_{ijab}^{\text{complete}}$, the function f must be identified. A restriction regarding this function f is required. Instead of a flexible, parametric or even non-parametric f that theoretically allows estimating the functional form of variable effects and interaction of variables, the parsimonious linear form is supposed (see Fig. 7). It does at least roughly approximate a substantial amount of the potential main effects of the variables. Each $a_k \neq 0$ therefore corresponds to the

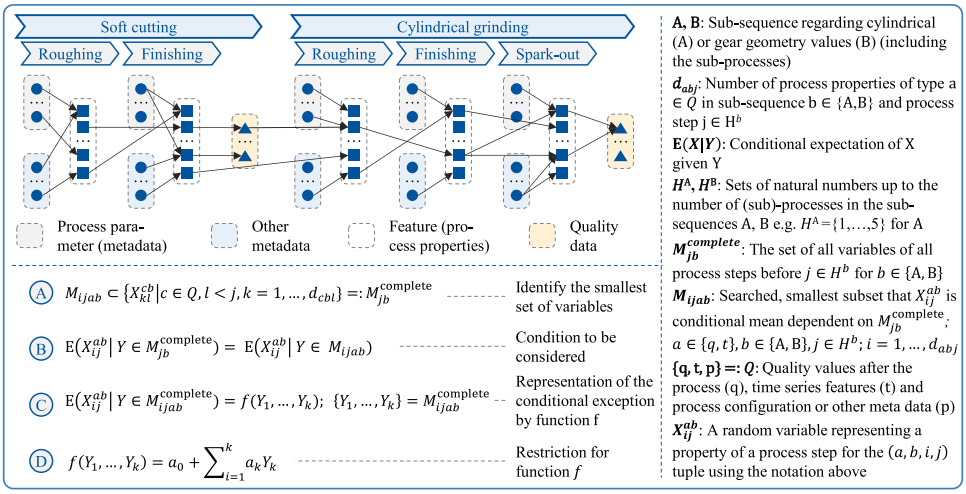


Fig. 7. An exemplary graph representing identified dependencies along the process sequence and formulae for the statistic modeling.

present dependency of the conditional expectation considered on Y_k, while $a_k = 0$ indicates that the direct effect of variable Y_k is mostly negligible. The variable can then be selected by considering each variable of type q and t of process step $i = 2, ...,5$ for both of the sub-sequences and executing variable selection for linear models with all variables of the steps $i' = 1, ...,i-1$ and the process parametermization parameters of step i.

Various methods for variable selection in a linear model set-up have been developed and can be taken into account for executing the selection in this case. Staerk et al. suppose that a homogenous linear model is valid for the response variable with a subset of the possible explanatory variable comprising the linear predictor [53]. As other algorithms, they consider a high dimensional problem. By adaptively selecting random subsets of all possible explanatory variables in an iterative algorithm, the model with the best value with respect to an information criterion, such as the extended Bayesian information criterion, is searched. The crucial assumption for the convergence of this method (i.e. that the set of selected variables converges to the best model in the aforementioned sense) is the ordered importance property. This means that the variables can be ordered such that if the first h variables are contained in this iteration's subsample, then they are selected in this iteration. This is not only a convenient assumption for the considered set-up: Staerk et al. also show that the algorithm still converges to a stable solution in comparison to established selection methods if this assumption is not satisfied. In conclusion, if the error term has approximately the same variance for all response variables in a single selection process, it is possible to extract a stable indicator for the most important process properties having an effect on the variable considered.

The described procedure results in a graph showing dependencies that can be extracted from the available data (cf. Fig. 7). Due to the complex selection procedure for a high dimensional set-up, one can assume that multiple false positive and false negative identifications are present. In the case of the experiments considered, partially independent data sets are available for multiple geometry features with similar processing (such as different bearing seats). Thus, the independent execution of these data sets allows for validation to a certain extent, as well as a critical comparison of the identified variables by comparing the results from the data sets. If the influence of a variable on the conditional expected value has a form which, when approximated by a straight line, results in a line with a slope close to 0, it is not expected that the variable can be identified by the procedure above. Likewise, several variables may have an interaction that is not identifiable here. This is why the methodology is limited in its ability to identify the dependencies between the (sub-)processes, nevertheless it provides an important basis for further research of cross-process effects and their influence on the design of optimal, economically or ecologically sustainable processes. In particular, as a graphical model between multiple random variables, the identified graphs provide a basis for causal inference, which can be used to estimate the causal effect of process phenomena and parameter settings on the final component characteristics.

The stochastic modeling of the cross-process dependencies presented here therefore provides the basis for developing applications that make use of the obtained knowledge to optimize the manufacturing process sequence in terms of economics and ecology. Different applications are presented below, which are based on the presented fundamentals of data management and cross-process dependencies, and which were investigated within the project.

Life cycle assessment

Until now, manufacturing processes were optimized solely in terms of economic (costs) and quality aspects [54,55]. Due to the advancing climate crisis, climate-impacting manufacturing process inputs and outputs such as energy consumption are increasingly coming into focus [56–60]. This will lead to a reduction in energy consumption, while other environmental impacts (such as eutrophication of fresh water, particulate matter pollution or the use of fossil resources) may continue to be disregarded. However, if the goal is to achieve a holistic ecological improvement, it is necessary to consider all the relevant flows which lead to environmental damage, regardless of whether they are caused by the (raw) materials or the manufacturing processes [60].

The challenge here is to collect the necessary information for an ecological analysis from each manufacturing process. Therefore, an increasing amount of secondary data exists in databases (e.g. Ecoinvent 2018 or ProBas 2000), but this data is often incomplete or is not representative due to the diversity of the industrial landscape [61]. In addition, there is a lack of methodical approaches to support the collection of information from manufacturing processes and link it with further information from experts or life cycle inventory databases in order to evaluate process sequences in detail. A method that allows users to combine primary data from manufacturing with secondary data from databases to calculate environmental impacts is therefore presented in the following.

This framework is based on the established method of life cycle assessment (LCA) standardized by DIN EN ISO 14040/44 [62]. It consists of the four phases: goal and scope, life cycle inventory (LCI), life cycle impact assessment (LCIA), and evaluation, and was applied to this database. For the purpose of evaluation, one manufactured component is defined as a so-called functional unit in order to enable comparability between different process designs.

After defining the objective and the scope of the LCA (phase 1), relevant information for an ecological evaluation must be collected in the second phase (LCI). This means that all material and energy flows which are relevant for the ecological description of the manufacturing process must be identified. Grünebaum presented a method for identifying the relevant material and energy flows for manufacturing processes [38]. Only primary manufacturing data was used for the energy flows. For this purpose, all machines were equipped with external electricity meters to measure the power consumption of the machines/processes and auxiliaries. With the help of metadata, the time series of the energy measurement is analyzed and assigned to the individual components and (sub-) processes. Moreover, the tools (and alloys) used were also taken into account as material flows. The different levels of tool wear caused by the various process parameters were extrapolated using technological data from similar experiments in the past. The data and information flows are illustrated in Fig. 8.

For the necessary secondary data (such as for evaluating the tool alloys), the Probas database from the German Federal Environmental Agency was used (ProBas 2000). The German electricity mix was assumed to elevate the energy flows. For the LCIA, assessment methods recommended by the UNITED NATIONS ENVIRONMENT PROGRAMM (UNEP) were used at the midpoint level (UNEP/SETAC Life Cycle Initiative 2016, 2019) [63,64]. By linking the measured energy and material flows with the ecological effects of these flows, the processes within the process sequence were evaluated individually and in relation to a component with regard to a wide range of ecological effects. The effects (partially approximated data) on the global warming potential and on particulate matter are shown in Fig. 9, where it is already implied that many other influences have been investigated.

The last step of the LCA is the final evaluation. In principle, a wide variety of evaluations can be carried out depending on the previously defined objective. In this case, the goal defined in the first phase of the LCA was to identify the most ecological process parameters for the whole manufacturing process sequence. Therefore, the environmental impacts of the individual experimental groups were compared. The environmental impacts the environmental impacts were divided into

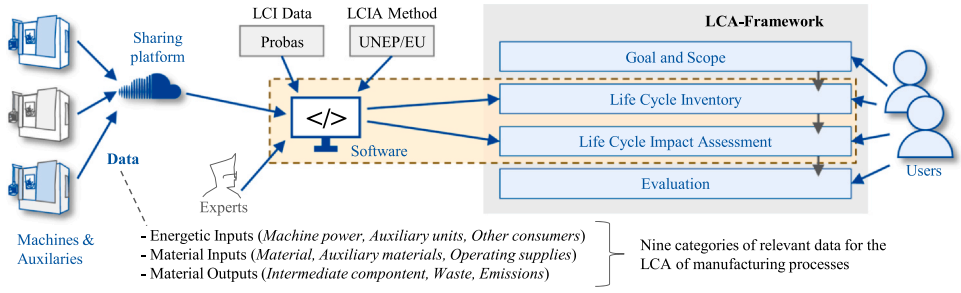


Fig. 8. Framework for ecological evaluation of manufacturing processes.

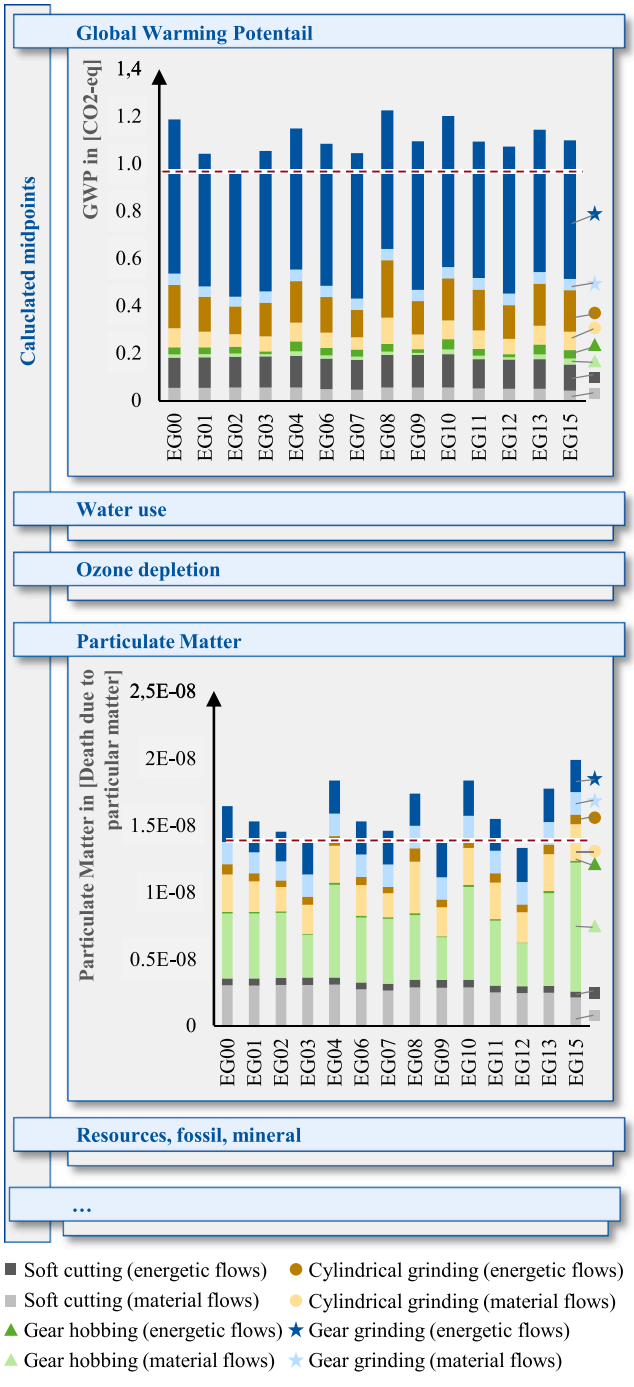


Fig. 9. Calculated midpoint (selection) from the manufacture of the pinion shafts.

those caused by material flows and those caused by energetic flows. Referring to the diagrams shown in Fig. 9, it is striking that more particulate matter emissions arise from the upstream supply chain of the material flows than due to the processes' energy consumption. The experimental groups EG03, EG09 and EG12 cause lower particular matter emissions than the other EGs. These three EGs have in common that no finishing process was used in the gear hobbing process, which significantly lengthened tool life. The evaluation shows that, as emissions are highly dependent on the raw materials in the tools, increases in tool life offer promising leverage for ecological optimization. The effects of this on the achievable quality or the economic result are shown in the following section on economic and ecological optimization. When considering the effect on climate change, the results are contradictory. The climate-damaging emissions arise primarily from the energy consumption of the individual manufacturing processes, as opposed to the upstream supply chain of the material flows. Gear grinding in particular requires a great deal of electricity due to long process times. Possible levers are the reduction of machining times (see EG02 with higher feed rate). The increased wear of the tools caused by such measures (higher process speeds with higher tool loads) could be accepted up to a certain point if one focused solely on the effects on climate change.

However, it becomes clear that individual ecological target values partly show opposing approaches to improvement. If additional economic, and particularly quality-specific targets (with their cross-process dependencies), are taken into account, this challenge is further intensified. It therefore becomes clear that ecologically target-oriented and holistic optimizations can only be achieved using the data generated by digitalized process sequences. It is also necessary for users to set up a target system and weight the different targets.

In the near future, customers will increasingly need to know the environmental impacts of their suppliers' products. This method provides a promising foundation for the environmental assessment of products through cross-process analysis. With further research, this method will be refined and automated to allow for industrial use. The goal is to have ecological assessments performed as standard and in parallel with other experimental analyses. The resulting database can then be used to increasingly improve ecological assessments and forecasts with regard to new processes.

Economic and ecological optimization

As mentioned in the introduction, competitive advantages for manufacturing companies result from the efficient production of their products/components with strong economic results, fewer negative effects on the environment, and reliable achievement of the required qualities.

In addition to the ecological impacts presented in the previous section, the costs of the processes and process sequences were also calculated. The calculation is based on the model for the calculation of production costs according to Klocke [65]. The production costs

determined for the individual EGs are shown in Fig. 9. These consist of the manufacturing costs (costs for the individual manufacturing processes) and the costs for the raw materials. The manufacturing costs include all expenses for the machines (based on the hourly machine rate, cf. Klocke's cost model), the personnel and tools including auxiliaries. The process times necessary for the calculation were derived from the collected data and assigned to the EGs. Tool life and tool changing times were estimated from the literature and in discussion with technology experts. For the formulas for determining the cost variables of the individual manufacturing processes, please refer to the model for evaluating production costs according to Klocke [65]. The costs for the other processes that were not investigated in detail, such as deburring or hardening, are summarized in Fig. 10. Further costs, such as transport or storage costs, were not taken into account.

The highest costs are incurred in the gear grinding process, and can be attributed to high process times and the resulting high machine costs. In contrast, in the highly automated gear hobbing process, the tool, which consists of high-speed steel, accounted for the highest proportion of the costs. The tool cost would decrease if a carbide tool were used. As Fig. 10 shows, EG12 leads to the lowest manufacturing process sequence costs. These low costs are due to the omission of the finishing process in both soft cutting and gear hobbing, and to an increase in the feed rate in cylindrical grinding.

If additional data related to component characteristics from the digitalized machine tool and testing machine measurements are taken into account, the suitability of EG12 must be relativized. The reason for this is that not all component characteristics can be reliably/reproducibly achieved. For example, in the manufacturing process sequences where the finishing process in soft cutting was omitted (EG11, EG12 and EG13), some of the manufactured diameters of the final shaft heels were outside the required tolerance. Here, the number of components of five per EG must be taken into account, since outliers or random errors can have an influence on the results and subsequent processes (see section on cross-process dependencies). Although the absolute values of the component characteristics are subject to uncertainty, the deviation of the characteristics between the individual EGs is so significant that very good comparative statements can be made with regard to the economics and quality. Accordingly, the most economical alternative is EG07 with a quality close to 100%. The settings included a higher feed rate and cutting speed for soft cutting, no dressing during the machining of a component and a higher feed rate for cylindrical grinding. This shows that manufacturing processes in process sequences cannot be designed individually, since dependencies between processes with effects on quality are not taken into account. These cross-process dependencies are explained accurately in the following section using the example of the soft cutting and cylindrical grinding processes.

Based on these findings, it also becomes apparent that targeted tolerance management has a high potential that can be explored by considering cross-process dependencies. The tolerances chosen in the experiments (both for the final and intermediate states) were derived from an industrial application. In particular for EG03, EG09 and EG12 (without a finishing process during gear hobbing and therefore significantly more cost-effective), a high percentage of the components did not meet the tolerance for the intermediate state after gear grinding. However, this had only a comparatively minor effect on the gear grinding and ultimately on the final component characteristics.

Motivated by the previous section on life cycle assessment, ecological targets must also be taken into account. Fig. 11 shows the manufacturing costs and the global warming potential (GWP) resulting from the manufacturing of a shaft as CO_2 equivalents as an exemplary environmental impact. The figure illustrates a correlation between production costs and the GWP. When one considers the input variables and significant influences on both variables, it becomes clear that high process times lead to both higher costs (higher machinery and personnel costs) and a higher GWP (due to the higher energy consumption of the machines). Nevertheless, a trade-off between ecological and economic targets is already evident here, e.g. EG02 represents the best GWP while EG12 represents the economic optimum. EG07 is the alternative with the lowest costs and GWP where quality is almost 100%.

In order to make a decision on the basis of the different target values and the different characteristics of the designed manufacturing process sequences, a target system is necessary which weights the different target values comparatively, e.g. by the analytic hierarchy process [39]. As explained in the state-of-the-art, there are various monetary weighting methods for integrated economic and ecological evaluation, which can be used as a target system. Due to the above mentioned criticism of the different monetary weighting methods, no monetary weighting is performed in this approach. However, the midpoints determined above form the basis for these monetary weightings, so that users can apply them directly according to their preferences. In order to ensure comparability with

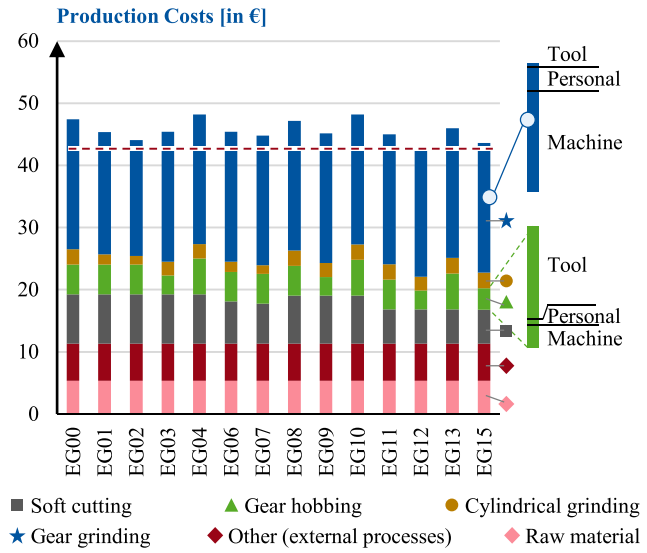


Fig. 10. Production costs for the manufacture of pinion shafts.

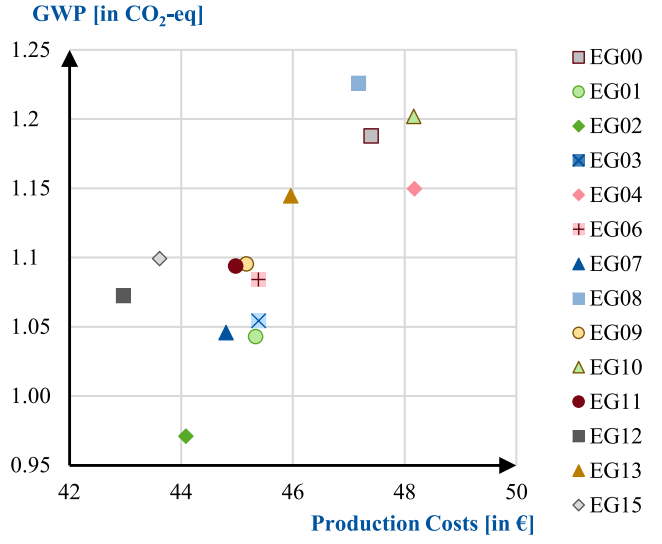


Fig. 11. Calculated costs and the resulting global warming potential from the manufacture of the pinion shafts.

regard to the ecological effects of manufacturing process sequences, it is therefore necessary to standardize procedures for recording the relevant energy and material flows as well as evaluation methods and to transfer them to a broad industrial application [66]. If quality, production costs and GWP were the only evaluation variables, the further procedure in the case study is to improve EG7 (alternative with the lowest costs and GWP where quality is almost 100%) in the direction of EG2 and EG12 until quality can no longer be ensured. In parallel, it must be investigated whether the quality of EG2 and EG12 can be improved by process adjustments.

Overall, the results of the economic, ecological and qualitative evaluation show that only an integrative approach can lead to a holistic optimum. For this purpose, manufacturing process sequences must be digitalized in order to collect all data (including relevant metadata) on a single platform in order to be able to use them for the various analyses. Here, the consideration of cross-process dependencies is of greater significance. For the holistic evaluation of the manufacturing process sequence, the test group size of at least 5 components per test group was sufficient. The analysis shows that the differences between the test groups were clearly evident.

Data-driven process optimization in grinding technology

In addition to the previous explanations about the evaluation of the process sequence and on cross-process optimization, the following section uses the grinding process as an example to show how digitalization also supports the optimization of individual processes. The external cylindrical grinding of the bearing seats (geometry features F04 and F41) and the geometry feature F09 of the pinion shaft was performed on a Studer S41 grinding machine. To achieve a mean roughness depth of Rz = 4 µm and diameter tolerances of Ø25h6 and Ø30m6, the grinding process was divided into a roughing and a finishing operation with subsequent spark-out for each shaft. Depending on the experimental group, the grinding wheel was dressed with a dressing plate before each grinding process/feature or only before grinding a new component.

The overall examination of the process sequence shows that the proportion of the machined volume in cylindrical grinding to manufacture the components was low at about 1% compared to soft cutting technologies such as turning (94%). In contrast, the proportional CO_2 equivalent of the grinding process was 44% higher than for the turning operations. In addition to the CO_2 emissions caused by energy consumption, corresponding emissions are also caused by the material used in the grinding wheel. The cross-process evaluation shows that a reduction of the dressing operations to one third of the reference process (EG00) resulted in significant CO_2 savings. In terms of the CO_2 equivalent of the process sequence, the three best experimental groups (EG01, EG02 and EG07) were those in which the dressing operations were reduced. Compared to the reference process, a CO_2 saving of over 15% was achieved by increasing the feed rate by 50% coupled with a reduction of the dressing operations to one third. As expected, the reduction of the dressing operations not only had an ecological but also an economic effect on the total costs of the process sequence.

The findings show that the optimization of dressing operations in grinding offers considerable potential for CO_2 savings and increased efficiency in industrial practice. Currently, the dressing process is initiated based on the experience of the machine operators in the industrial environment. Dressing processes are initiated at an early stage to prevent wear-related scrap due to loss of component dimensions, increased surface roughness or thermal microstructure damage. A significant reduction in process performance is accepted, and precisely this offers considerable potential for optimization.

In order to shorten production times, save tool costs and improve the ecological footprint of the grinding process, the automated, data-based determination of the dressing interval is a promising solution. Appropriate approaches (e.g. for determining tool changes in soft cutting) are highly relevant for a wide range of technologies. Within a data-based approach, sensor and machine control data are used as input data for process models to, for example, predict component surface roughness or identify microstructural damage. As input data, the acoustic emission or the power of the grinding spindle can be recorded as a time series and can be analyzed by the extracted time series features. On the process model side, supervised machine learning models for classification or regression offer the potential to determine the result variables. The application of these process models within a software tool enables in-process monitoring of the process result variables and therefore a result variable-specific determination of the dressing interval. By predicting the process result variables during grinding, it is possible to optimize the number of dressing operations in terms of economics and ecology in such a way that an increased number of components are produced within defined tolerances and thermal microstructure damage is prevented. The prerequisite for this is a digitalized manufacturing process as presented in this paper.

In addition to the sole consideration of the external cylindrical grinding process, it was determined that the grinding process output was significantly influenced by the preceding soft cutting operation despite an overall allowance of z_{ges} = 300 µm and an intermediate hardening process. Fig. 12(A) shows an example of the measured diameters of feature F09 after the cylindrical grinding process. The diameters after grinding refer to the experimental groups EG00 (reference process), EG08 (soft cutting with worn tool) and EG11 (no finishing during soft cutting), while the reference process design was used for cylindrical grinding. The evaluation shows that the process variance was lowest for the reference soft cutting process. The use of a worn tool during soft cutting leads to an increased process variance and a shift towards smaller diameters. The elimination of the finishing process (in soft cutting) with a constant allowance of z_{ges} = 300 µm had the greatest influence on the diameters after cylindrical grinding.

In this case, the process variance increased more than fourfold. This shows that the input variables for grinding depend on the turning operation, and different process conditions for the cylindrical grinding process could therefore also be observed in the process condition variables for the roughing and finishing operations. The diagrams in Fig. 12(B) and (C) show a principal component analysis (PCA) of the grinding roughing and finishing operations. Here, the principal components X1 and X2 represent the dimensional reduction of selected time series features of the root mean square (RMS) of an acoustic emission signal. The signal was recorded by an acoustic emission sensor mounted to the grinding spindle. The time series characteristics were selected by a feature selection based on the determination of the mutual information and chi-square of the time series features. The PCA shows clear clusters for the different experimental groups, especially for the roughing operation. In addition, the diagram (B) indicates that the cluster of EG08 is arranged closer to the cluster of the reference process than EG11. It therefore shows a higher similarity to the reference process. The PCA of the finishing process (cf. Fig. 12(C)) shows that the clusters of the individual experimental groups are arranged more closely and partly overlap. However, it is still possible to differentiate between the experimental groups.

The results of the investigations illustrate the dependencies of successive manufacturing processes within a process sequence. These dependencies can also be at the detailed level of component quality. The evaluation of machine control and sensor data offers the potential to identify disturbance variables deviating from the reference process during roughing in order to make short-term changes in the finishing process to maintain component tolerances. In addition to the detection of disturbance variables from previous

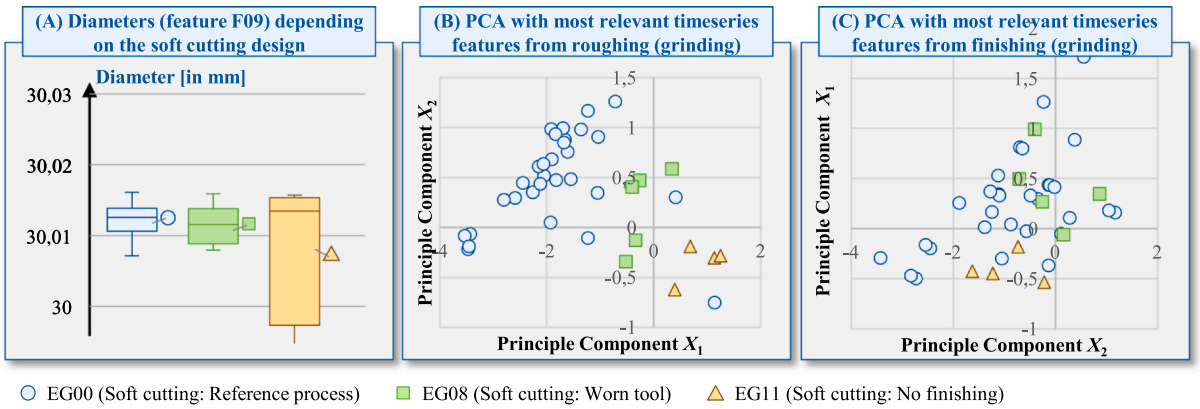


Fig. 12. Principal component analysis for the grinding process.

manufacturing processes, it is also possible to react to material or tool dependent process changes. For example, a data-driven grinding process control offers the potential to compensate for hardness fluctuations within batches of component blanks or grinding wheels. To further investigate the observed effects, derive data-based optimization methods, and validate the results obtained so far, larger amounts of data than those generated in these experiments are required. This also applies to the development of the statistical model as well as future topics to be addressed, such as predictive quality. Therefore, new experiments will be carried out on the basis of the acquired findings, which will enable the further development of such methods.

Conclusion and outlook

This research work investigated the potentials of data-based evaluation and optimization of manufacturing process sequences and the challenges that have to be overcome in order to realize the potentials. The approach covers the phases of data generation, data preprocessing, data storage and sharing (together addressed as data management) up to the data usage. In data generation, the process sequence under consideration was described as well as the underlying experimental design, which is a prerequisite for data-based analyses. Regarding to the data management, it was explained how the various types of data from different sources were structured and stored in a uniform way. In data usage, this enabled the holistic data-based evaluation of the manufacturing process sequence. The described methodology made the data-based evaluation of the manufacturing process sequence possible, both economically and ecologically (LCA), as well as in terms of quality (quality measurements). For the authors, the holistic data-based evaluation of manufacturing with regard to the different target dimensions represents the first step in the data usage phase. In the next step, methods to optimize the manufacture by using data are gathered. It was analyzed which of the experimental groups showed particularly promising results and thus contributed to an optimization of the process sequence as a whole. The results of the economic and ecological evaluation as well as the quality were included in this analysis. For further cross-process data analyses, it was described how a statistical model must be set up in order to identify cross-process dependencies. Additionally, it was shown for the grinding process how a data-based optimization can look like by identifying the influences of preceding manufacturing processes from the process data in order to be able to react specifically to the disturbances.

As the research results demonstrate, the digitalization of manufacturing process sequences in combination with innovative data-based methods offers great potential for science and industry. Thanks to the promising results, highly positive feedback from industry and the large number of research questions raised, the investigations presented in this paper form the starting point for future interdisciplinary research on the digitalization of manufacturing process sequences. In the next steps, data management has to be improved in order to collect, process and store manufacturing data more efficiently and enable the automation as well as the usability of the developed methods. Furthermore, detailed investigations and the development of suitable data-based methods for analyzing cross-process dependencies will be carried out in order to quickly identify and explain these complex, technological relationships. For improved and holistic LCA, data pertaining to component use (current experiments on digitized test rigs) will be integrated into the analyses as well as expanded on using circular economy concepts. In addition to the use of data for post-production analyses, the digitalized manufacturing process sequences will be used for process monitoring, e.g. to develop innovative approaches for process certification. In the medium term, the digitalized manufacturing process sequences and the combination of the developed methods will contribute to the implementation of innovative approaches for predictive quality and to the generation of digital twins for individual components, which will make online forecasts possible in terms of quality, economics and ecology.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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