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Part Variation Modeling to Avoid Scrap Parts in Multi-stage Production Systems

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Abstract

Manufacturing systems for today's products are complex systems requiring a variety of different processes in order to be able to manufacture all necessary part features. This also applies to the production of rotating components, which have experienced increasing demand at the latest due to the growth in mobility. As in almost every manufacturing process, quality-reducing defects can occur due to deviations for example tool wear, which cannot always be avoided. Those, that have accumulated from previous process steps can cause the occurrence of superimposed defects. This leads to complex relationships between quality defects in the end product and the numerous parameters of the manufacturing processes. To remain competitive, production must be optimized in order to identify defects as early as possible, as well as their dependencies and variation patterns. The paper presents an approach to identify and model part variations within multi-stage production systems. Subsequently, based on a detected deviation, a downstream compensation strategy can be proposed at an early stage of the manufacturing process, which uses the capability of the overall system to fundamentally eliminate rejects.

Keywords: Zero-defect Manufacturing; Defect Compensation; Multi-stage Production System; Downstream Compensation

1. Introduction

Increasing digitization in today's industry and society is driving a shift towards data-driven production. At the same time, the demands on companies are increasing in terms of individuality and the efficient and resource-saving production of high-quality and complex products. On the one hand, this increasing market and customer orientation is changing the understanding of quality, and on the other hand, it is also increasing the demand for quality in production [14].

Manufacturing facilities for today's products are complex systems, often multi-stage production systems, that require a variety of different processes in order to be able to create the product with all the required features This also applies to the production of rotating parts, which have experienced an increase in demand due to the rise in new mobility [13]. Rotating components are particularly necessary in the aerospace sector, in rail transport, and for drive units in the automotive sector. The requirements for the components are primarily determined by the intended use. In the aerospace sector in particular, enormously high requirements have to be met in terms of product quality, functionality (lightweight construction), and safety. The multi-stage production process for a turbine shaft is correspondingly complex, see Fig. 1 showing the relevant production steps of such a shaft.

From an internal study, it is known that for the example component, the net production time is 60 h to 90 h [4]. In reality, the component passes through 13 machines with up to 30 machining processes in which first the inner contour and then the outer contour is produced [5]. This is followed by the end-of-line quality control (EOL), which is widely used for rotating parts as confirmation of the requirements. Thus, correctness is only checked at the end of the entire production chain. This special quality control involves, among other things, setting the component to the critical speed of about 5500 rpm, to check the

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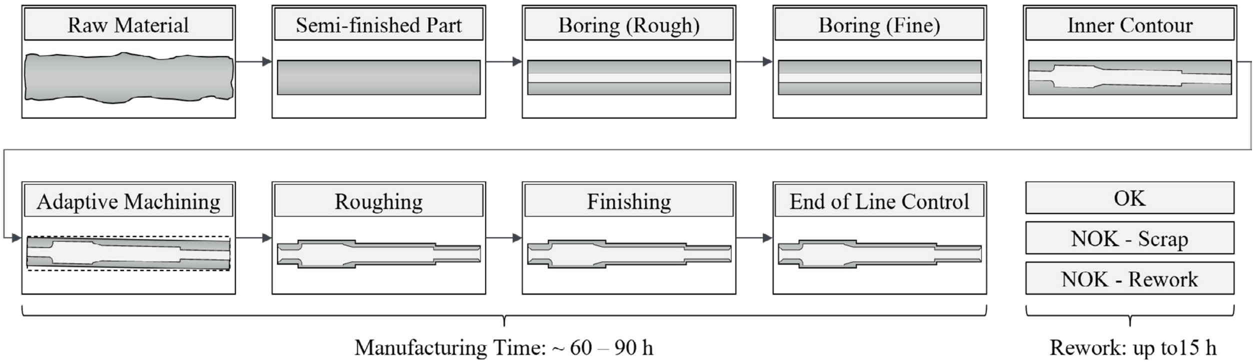

Fig. 1. Demonstration case: manufacturing process of a hollow turbine shaft (dark gray is work piece material, light gray is removed material of the inner contour) [5].

shaft for imbalances. Even if the component has ideal external dimensions within the tolerance zones, this often does not mean that the component is free of unbalance. Defects that lead to unbalance and thus to scrap are not uncommon, and late detection of defects results in unnecessary waste of time, material, and energy during production. In many cases, however, the unbalance lies within a tolerance in which the component can be reworked at defined stages. However, rework i.e., material removal based on the measurement results, is an iterative process of up to 15 h which means up to 25 % of the total production time.

The fact that dimensional defects cannot always be avoided or detected directly in the process is described by Westkämper [15], Jiao and Djurdjanovic [9], Zhang et al. [16], Abellán-Nebot et al. [1], and more recently by Reiff et al. [12], Magnanini et al. [10] on the basis of different multi-stage production systems. Zhang et al. see this as a fundamental problem and underpin the need for modern, even individual solutions in some cases. Defects mainly occur in the form of dimensional and shape deviations due to e.g., tool wear, frequent re-clamping, as well as vibrations on the workpiece caused by the high machining forces. Deviations that have accumulated undetected from previous processes can cause the occurrence of new defects. This leads to complex relationships between quality defects in the final product and the numerous parameters of the manufacturing processes.

Competitive production must be optimized to detect defects, their dependencies and development patterns as early as possible. This was the goal of ForZDM, an EU-funded research project that has fundamentally rethought previous approaches to production planning and also existing manufacturing processes between 2016–2021 [4]. In addition, a cost-effective and flexible design of manufacturing systems has been created using state-of-the-art methods and technologies, with the aim of realizing production that can detect defects at an early stage and does not allow defect propagation, as well as does not require time-consuming rework or even produce rejects – Zero Defect Manufacturing (ZDM). Multi-stage production systems are predestined for this; due to the multitude of processes and their complexity, they provide a high probability of error occurrence, but on the other hand also the possibility of being able to compensate for these in the further production process through the capabilities of the overall system.

To exploit this potential, this paper presents a method to identify and model part variations along the material flow that lead to scrap or rework, and then to enable the right strategies for inline compensation or prediction based on specific incidents. In our case different geometrical and dimensional deviations and their combination at the shaft lead to time and cost intensive and not sustainable rework. Each of these combinations forms a PVM mode that must be avoided in the future. The paper is structured as follows: In Section 2, the state of the art is presented. Section 3 describes the developed method and is completed by a final verification with a validation on the demonstration case described in Section 4. In Section 5, conclusions are drawn and an outlook is given regarding further potentials of the presented method.

2. State of the Art

In the past, the focus in optimization of multi-stage production systems (MPS) laid on consideration of individual and separate processes using static process control systems. The potential inherent in the inter-stage relationships, which among other things are the cause of defect generation, but can also be used to compensate for defects, remains unexploited. Moreover, traditional approaches consider the aspects of product quality and process capability separately [11]. The interplay, however, is seen by Colledani et al. [2] as the most recent paradigm and the basis for implementing ZDM. As early as 1998, Fong and Lawless [7] explicitly derived mathematical models capable of capturing and describing component variations along a MPS in order to subsequently apply compensation strategies. Based on this, the stream-of-variation (SoV) theory was established, which additionally includes multivariate analyses for failure diagnosis and prediction [8]. Magnanini et al. [10] extended the SoV theory and implemented a control model which allows defect compensation in downstream processes for MPS.

However, previous approaches do not take into account the characteristics of a manufacturing process of rotating components. In addition to dimensional deviations, geometric deviations must also be taken into account. These can be described with the help of a parametric model for rotating components established by Eger et al. [6]. This model was also the fundamental part for developing two individual compensation methods for geometric and dimensional deviations previously presented by Reiff et al. [12] and Eger et al. [5], respectively. The method presented in this paper is a combination of both methods i.e., modeling and identification of part variation models and their compensation in terms of geometric and dimensional deviations.

Further, existing approaches are limited if the description of the component's variability, which among other things also contains information about the defect origin as well as the interstage relationships, is missing [3]. For the practical implementation of a ZDM and the associated part variation modeling in MPS, so-called Part Variation Modes (PVModes) are developed here in this paper, which describe certain part variations of rotating parts as described in the following chapters.

3. Identification and Modeling of Part Variations

In order to avoid rework and scrap parts it is necessary to prevent the production of defective parts at an early stage. However, this is not always caused by exceeding individual tolerance limits, but can also be induced by accumulated deviations or non-obvious dependencies in multi-stage production. For this reason, it is important to identify patterns in production and thus determine dependencies in the production of defective components. Based on the identified patterns, PVModes can then be defined. By early recognition of an occurring or an occurred PVM, it is possible to initiate countermeasures in the form of compensation strategies and to avoid the production of a otherwise defective part.

For the definition of PVMs, a distinction is first made based on the type of deviation that has occurred: geometric or dimensional. A geometric deviation refers to a discrepancy between the axis of rotation of the part and the actual axis of symmetry. If these two axes do not align, it results in imbalances and errors in subsequent production due to dependencies of the component radii and the actual angle of the clamped component. Geometric deviation are further divided for solid and hollow shafts.

In the case of a hollow shaft, the deviation can thus relate to the outer as well as the inner contour and is defined based on the resulting shape. For example, the deviation can describe a parabolic, exponential or sinusoidal shape. Dimensional deviations, on the other hand, refer to a difference between nominal and actual values of the manufactured dimensions (e.g., diameters and lengths). In this case the assignment to one (or more) PVM is made on the basis of the previously identified patterns in e.g., the multi-level dependencies. Here, it is checked whether the deviation that has occurred is part of such a pattern that has previously led to the production of faulty parts.

For comprehensive identification and modeling, possible correlations between dimensional and geometric deviations must also be taken into account. Only then can a holistic statement be made about the dependencies in multi-stage production. For example, a certain form of geometric deviation can lead to dimensional deviations due to eccentricity in very specific production steps. It is thus necessary to consider the identified geometric deviation as additional information for the modeling of PVMs as well as the subsequent determination of downstream compensation strategies.

3.1. Method Requirements

The identification of these PVMs for the subsequent modeling of the PVModes requires the use of suitable algorithms from the field of machine learning. Due to different types and specifications of variations described before, different requirements for the algorithm arise. A fundamental requirement for the choice of algorithm is the ability to detect dependencies across multiple stages of production. Only then is it possible to reliably predict the effect of accumulated deviations. For training the algorithm recognize these dependencies, or patterns, production data from the described use case are available. This includes measurements of various sensors at all processing steps as well as measurements of the end of line control and thus also the information whether a good or faulty part has been produced. Accordingly, labeled data sets are available, which makes an algorithm from the field of supervised learning suitable.

Another requirement for the algorithm is the handling of different data types. The reason for this is the consideration of dimensional as well as geometric deviations. Dimensional deviations are characterized by a single measured value of a sensor, whereas geometric deviations are described by several single values that have to be considered coherently.

3.2. Identification and Modeling Method

Taking into account the requirements for the algorithm as well as the goal of identifying part variation patterns, a multistep procedure was designed. This can be roughly divided into the two steps of data preprocessing and model building shown in Fig. 2. Data preprocessing has the goal to increase the prediction accuracy as well as the reliability of the algorithm before it is learned based on the data.

In the method used here, the first step is to classify the geometrical shape of the part. Here, a shape is assigned on the basis of interrelated measurements along the axis of rotation, depending on the extend of the deviation from the centre axis After that, data preprocessing consists of transforming the sensor values, eliminating data sets with insufficient entropy, filling in missing values, adjusting the ratio of good and faulty parts in the data set, and finally converting the data into categorical values. The initial transformation of the sensor values serves to be able to account for tolerance violations of the sensor values in the analysis. The resulting normalized sensor values thus describe the degree of deviation from their respective nominal values, or for geometric deviations, the characteristic of the assigned shape. For dimensional data a normalized value of 0 means, set-point and actual value of the sensor value match while a value of ± 1 indicates production directly at the upper, respectively lower, tolerance limit. If the absolute amount of

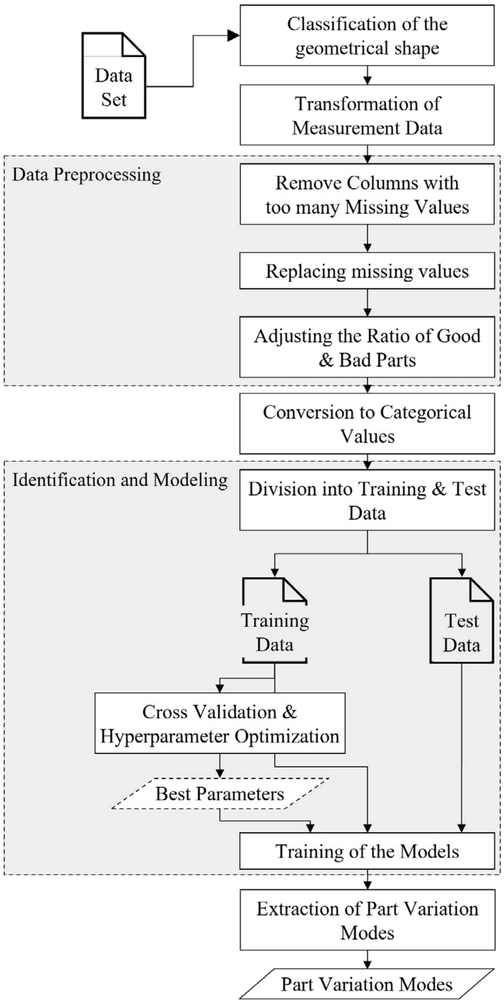

Fig. 2. Procedure of the developed method.

the normalized value is greater than 1, this corresponds to an exceeded tolerance.

If there are too many data sets with insufficient information i.e., too many missing sensor values, this can lead to deterioration of the expressiveness of the algorithm. For this reason, data rows with too little informative value are removed. Another executed step is the addition of values that are still missing afterwards. Otherwise, the choice of possible algorithms would be limited, since many machine learning algorithms require fully populated data sets. Equally problematic for algorithms can be a too unbalanced ratio of positive and negative examples during learning. In an actual production setting, however, the number of good parts produced outweighs the number of faulty parts. In order for the algorithm to not be affected by this in its efficiency, random data series of produced faulty parts are duplicated and thus the ratio is adjusted. Since the majority of algorithms cannot be applied to continuous values, the (normalized) sensor data x are discretized. Here, these are divided into a total of eight discrete categories on the basis of the respective mean value ($\bar{x}$) and the standard deviation (σ_x).

The data preprocessing is followed by the actual modeling of the algorithm. In a first step, the available data is divided into a training and a validation data set. The algorithm is trained on the basis of the training data set i.e., it attempts to identify relationships and dependencies in the data independently. In the case of already classified (labeled) data, the algorithm is able to correct itself in the case of false statements and thus optimize its expressiveness.

After the training phase is completed, the learned model is validated using the data set that was previously unknown to it. From the predictions made by the algorithm, metrics can be determined about its predictive capability and accuracy. To increase these metrics, two additional steps were performed in the applied method: hyperparameter optimization and cross-validation.

In hyperparameter optimization, all combinations of possible parameters are used for the predictions to determine the best parameter combination. Cross-validation, on the other hand, is intended to prevent overfitting of the algorithm to the data set used. Here, the training data set is divided into equal-sized parts, one part of each of which is used for internal validation during training. These two methods thus allow for an exploratory analysis of the possible solution space of the parameters and an increase in the generality of the algorithm.

The final model is ultimately used not only to make predictions about current production, but also to model part variation modes. These represent the dependencies and interrelationships of the multi-stage production identified by the algorithm. This means that potential production errors can be pointed out at an early stage and preventive countermeasures and compensation strategies can be initiated accordingly.

3.3. Evaluation Based on Real Data

The selection of a particular algorithm for model building was done by evaluation. For this purpose, various possible algorithms were compared with each other on the basis of different criteria. In addition, the following variants of the procedure were applied for each algorithm, resulting in eight possible combinations in each case:

1. With and without transformation of sensor values to a normalized value (T),
2. Replace missing values with the mean value / nominal value (M),
3. With and without discretization (D).

The metrics used for evaluation are, on the one hand, the achieved prediction accuracy and, on the other hand, the so-called F1 score. This provides information about the precision and robustness of a model.

For our evaluation, real data from a production line is available comprising measurements of the component from various data sources in production. Such data are manual and inline measurements as well as the unbalance determination in the EOL control. In total, the data set used contains 141 columns i.e., measurements at the stages (a data series denotes a single component in each case).In the data preprocessing, measurements with insufficient information content were first elim-

Table 1. Results of the evaluation.

Algorithm	Variant			Accuracy	F1-Score
	T	M	D	%	%
Random Fores	No	Mean	No	**81.48**	80.23
Decision Tree	Yes	Mean	Yes	**81.48**	79.77
RuleFit	No	Mean	No	80.95	78.31
K-Nearest Neighbor	Yes	Nominal	No	80.95	77.78
SVM	No	Nominal	Yes	80.42	**83.70**
Neural Network	Yes	Nominal	No	78.31	77.60
Logistic Regression	Yes	Mean	Yes	74.07	72.32
Naive Bayes	Yes	Mean	Yes	70.37	65.85

inated. As limits for the minimum number of rows with values 75 % was set. Furthermore, the number of rows classified as faulty parts was doubled by duplicating randomly selected ones to finally obtain a ratio of 315 good parts to 314 faulty parts. In this way, more balanced training data is available to the algorithm. In addition, hyperparameter optimization was performed for each algorithm with appropriate algorithm-specific parameters in each case, as well as cross-validation with a split into 5 equally sized data sets. A total of 8 different algorithms were compared for the evaluation. The best result of each algorithm depending on the combination of options of the method is shown in Table 1. Based on the comparison, it can be seen that the Random Forest and Decision Tree algorithms achieve the best results in terms of prediction accuracy. Whereas the SVM (Support Vector Machine) algorithm has the highest F1 score. In addition, five of the eight algorithms achieved their respective best results when the transformation of the sensor data to a normalized value was performed. This ratio also applies to the mean value as a variant for filling missing values. In the end, the decision tree was chosen due to the fact that the desired part variation patterns can be extracted directly from the decision tree model. The patterns here correspond to the individual paths along the tree from the root to a predicted faulty part. The paths thus describe the dependencies of the multi-stage production based on their respective rules.

4. Practical Validation

Data from approximately 600 turbine shafts, each with about 140 component descriptive parameters, were available for analysis. For confidentiality reasons, units are scaled and data abstracted, but they reflect the real scenario. The analyses show that deviations occurring along the manufacturing process can be limited to geometric, dimensional and surface defects. As shown in Fig. 3, it is the combinations of deviations that lead to component rejects at the end of the line. In addition, the consideration of geometric and dimensional deviations and their combination make up a large part of the PVModes. In the figure only a small part of the identified PVModes is illustrated in order to show the success of the Part Variation Modeling.

Already in the early machining steps (inner contour), undesired deviations are introduced into the component, based on the results from Eger et al. [5], which are directly related to imbalances detected during EOL and thus reject components. For the purpose of this paper, the dimensional deviations are clustered as patterns as mentioned earlier to allow for analysis with the dimensional deviations. These deviations are than clustered into exponential and linear deviations and their expression.

If one of these patterns occurs, the compensation of the eccentricity can be done in the following CNC machine based on different algorithms to achieve an unbalance-free part at the end of the MPS. However, this procedure does not guarantee that deviations will occur in the subsequent machining steps, which will continue to affect the compensated problem.

Based on 600 test shafts, the dimensional deviations can be related and modeled within the decision tree as PVModes. Blue circles in Fig. 3 show that such an influence is not exclusively due to a deviation, but can also be caused by the inter-stage accumulation of parameters within given tolerances. The example causes a large imbalance in the EOL and too much rework. Such correlations can only be identified from historical data and must subsequently be controlled for both error prevention and error compensation in the future.

A pattern that has already been detected must never reappear in its entirety in the production process, as it would, in the worst case, mean a scrap part. For this reason, all component variation patterns are described as a model by means of influencing and to-be-influenced parameters and monitored on-line accordingly. If a pattern or PVMode now appears, preventive measures, which result from the feature tree and the inter relationships, must be initiated. In addition to PVModes that depend on several processes, there are also individual modes as marked with green triangles in Fig. 3. If a value outside the upper tolerance occurs, the MPP usually offers the possibility to compensate the deviation along the material flow. The example of a diameter that is too large is used to see where the feature can be corrected by adjusting process parameters. Such parameters may be CAD parameters or machine code (G-Code) used during machining of the component (where applicable). The models describing the PVModes are adapted in a regular cycle of ten components in order to be able to react quickly to new conditions. In addition, the system is also analyzed and improved across components by transferring and examining the knowledge gained to other component variants. This also makes it possible to significantly shorten the start-up phase for a new component variant. Also with regard to optimization, or parameter adjustment, so-called part-to-part optimization is carried out in order to improve and control critical processes in the cycle of a component.

5. Conclusion and Outlook

The present paper describes a methodology which allows identification of inter-stage dependencies (PVMs) using machine learning algorithms to capture part variation modes with different aspects. By pooling geometric deviations, which occur very frequently in rotating components, it is now possible to model PVModes between geometric and dimensional deviations. By assigning the current production to a PVM, countermeasures in the form of downstream compensation strategies

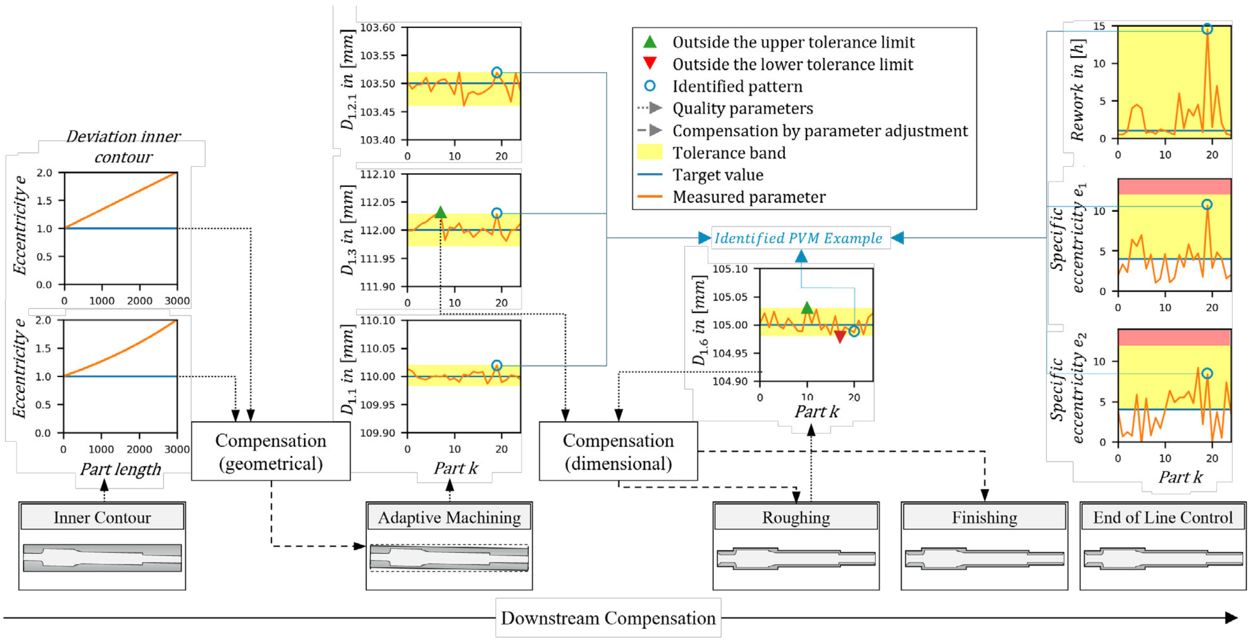

Fig. 3. Schematic workflow of the identification of PVModes with example and the accompanying downstream compensation.

can be initiated at an early stage. The developed method was also evaluated on the basis of real production data and its functionality was demonstrated. The method thus represents a step towards achieving zero-defect manufacturing within the field of rotating parts.

In the future, the method will be used in compensating faulty production of other rotating parts e.g., electrical motors where number of parts is higher and production time is lower. We further extend the method and use it on a digital twin after the production line's virtual commissioning, performed in the project SDM4FZI. By adding disturbances on the digital manufacturing process, dependencies can be already identified on the digital twin and can be than validated within the ramp-up phase of the physical manufacturing system.

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