Part Variation Modeling in Multi-Stage Production Systems for Zero-Defect Manufacturing

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***Abstract*—Multi-stage production systems concede for low error and failure margins within every single machining and assembly step to not degrade product quality. Especially during multi-stage production of rotating parts, minor defects during a single step can corrupt a workpiece beyond repair. Since multi-stage production systems are complex, inter-connected chains of machining steps, a global approach to handling and compensating error emergence and propagation is for reaching Zero-Defect Manufacturing indispensable. We introduce Part Variation Modeling within a knowledge capturing platform to monitor centrally gathered metrological data for deviations. Further, a parametric model is presented allowing for description of rotating parts and enabling identification of deviations at every stage. Based on our inter-stage correlation analysis technique, the parametric model enables description of Part Variation Modes of a piece given current machine states and historic deviation likelihood as will be presented.**

***Index Terms*—Production Systems, Intelligent Manufacturing, Data Analysis**

I. Introduction

Manufacturing lines of modern day products are complex systems with a multitude of different processes. Challenges arise from ever decreasing product life cycles and increasing customization implying high product quality for every piece and at every moment during production. For products of batch size larger than a single piece, like rotating parts such as shafts found in drive trains of electric rail-borne vehicles or airplane turbine shafts, high demands are put on quality, safety, and functionality. These requirements must be met during any stage of the production line to avoid errors propagating and rendering a workpiece beyond repair. However, only end-of-line quality checks are performed to meet customers' requirements, ultimately rendering the component unusable in case of defects [1]. Scrap material is not uncommon and, as a result of late detection of defects, an unnecessarily large amount of time, material, and energy are lost during fixing of known defects. In multi-stage production systems, dimensional and geometrical deviations occur in every phase of machining due to various sources of variation, including raw materials variations, the reference value used, the clamping position, and the machine tools in itself [2].

Starting in the 1990s, increasing complexity of multi-stage production systems has thrown up inter-dependency of product quality characteristics among process stages. Research efforts derived explicit mathematical models able to capture the flow of dimensional errors to use them for error reduction and compensation strategies [4–6]. The most common model is the so-called Stream of Variation (SoV), integrating control theory for design and control purposes with multivariate statistics for error diagnosis and prediction [7–9]. SoV is based on a state-space representation of a single component throughout all process steps [10–12], and has been widely used to identify sources of dimensional errors based on distributed measurements along the process stages [13, 14], to optimally allocate tolerances [15], or to analyze the measurement schemes in both the ramp-up phase and steady-state phase [16]. Reduction of dimensional variation of the final product may be attained by means of SoV techniques, or the more traditional statistical process control, with some differences related to the root-cause identification model and diagnosis features [17].

Moreover, when dealing with sensor allocation, being able to evaluate the information gathering capability of distributed measurement schemes is of great importance. Indeed, the optimal allocation of measurements, coined measurement strategy, is based on data that distributed sensors are able to gather [18, 19]. On the other hand, information that is valuable for an optimal ZDM-oriented strategy comes from many different sources, and it may include operators' feedback, process parameters, final product features [20]. In this context, the methodology used for quality control defines the capability of manufacturing strategies aiming at quality improvement of both, product and process. These methodologies establish prediction of deviations from mathematical models in order to define optimal forward-strategies for improving key product characteristics [21]. In fact, compensation strategies [22], adjustment procedures [6], and inspection strategies [1], are defined for downstream stages to close the loop of quality control.

With all models requiring extensive engineering skills to parametrize and put to use, there is no common strategy for implementing one methodology or another. Most commonly, during ramp-up phase, the statistical data of deviation induction for each process is acquired and consequently used for parametrization, from which defect compensation control is derived. A more simple approach, as presented in this paper, is based on on-line observation of the process to analyze,

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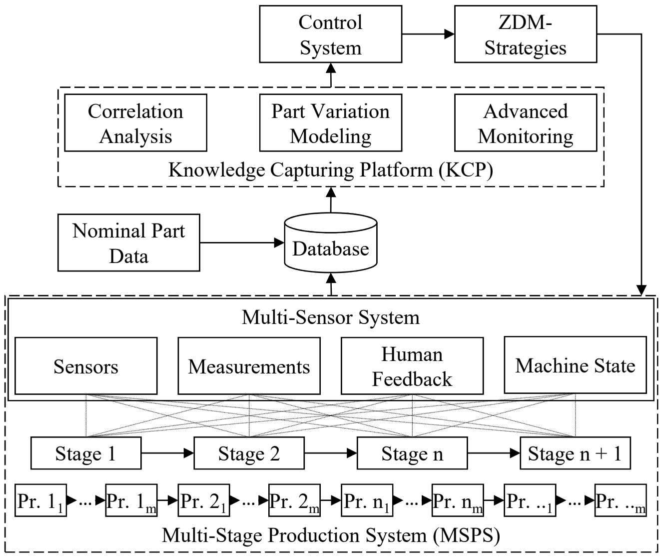

Fig. 1. ForZDM Architecture for reaching Zero-Defect Manufacturing within Multi-Stage Production Systems

structure, and visualize defect emergence and propagation, yielding manufacturing strategies for immediate corrective actions. In order to achieve this, we develop an "Integrated Zero-Defect Manufacturing Solution for High Value Multi-Stage Manufacturing Systems" ("ForZDM", funded by the European Union within the Cluster Horizon 2020) [23]. Zero-Defect Manufacturing (ZDM) is achieved by combining sensor readouts, visual inspections, or manual measurements at every production stage in a centralized database. This data serves the Knowledge Capturing Platform (KCP) providing the shop floor with decisions on how to compensate defects before they propagate down the line (cf. Figure 1).

We structure our paper as follows: in Section II, we give an overview on the project "ForZDM" with its architecture. Section III covers our concept of Part Variation Modeling and the implementation of the parametric model, serving as the basis for identification of dimensional deviations as presented in this paper. Requirements for the implementation of this approach, possible industry workflows and the main components for a holistic comparison of actual and nominal values are outlined in the same section. Lastly, we present and discuss results in **??**, also offering conclusions and future prospects of our concept of PVM.

II. Knowledge Capturing Platform

ForZDM aims at developing and demonstrating next generation ZDM strategies capable of dynamically achieving production control solutions for multi-stage system. We develop our multi-stage solution proposal on three different production lines: for jet engines shafts, medical micro-catheters, and railway axles [23] with the focus of this contribution on jet engine shafts and railway axles. These lines provide the basis to deploy specific contents of our solution and serve as pilot cases to demonstrate applicability to very different multi-stage production lines.

The architecture on which the solution proposed is based can be divided into four areas (cf. Figure 1) in which the first layer represents a multi-stage production system. In order to implement the ForZDM approach, more transparency must be provided within each production stage by equipping process stages identified as being critical to product quality with additional sensor systems. A comprehensive data acquisition system (Database), which characterizes the second layer, is able to collect different types of data from part and process describing sources. Next to additional sensor systems, manual measurements, visual feedback by the operator, and machine state, data is collected and extended by, nominal part from CAD-files and manufacturing tolerance information, i.a.. Knowledge must be extracted from all available data to identify causes for defect generation and their propagation mechanisms along the production line. Consequently, we introduce a knowledge capturing platform (KCP) as third layer, able of extracting knowledge from collected and filtered data with inter-stage correlation methods (correlation analysis, [24]), part variation approaches (part variation modeling) along the line and intelligent monitoring systems (advanced monitoring, [25]). We achieve this knowledge extraction by means of statistical and analytical methods, monitoring and diagnostic tools, and the implementation of a parametric component-feature model. KCP forms the interface between database and layer number four, a control system using the extracted knowledge to apply ZDM strategies.

III. Part Variation Modeling

Spread and accumulation of error lead to reduced product quality over time which, very often, is only detected during end-of-line checks. This ultimately causes a loss in guarantee of quality and, possibly time consuming, rework. ForZDM aims at identifying and understanding the variations of manufactured pieces in multi-stage production systems by means different to conventional methods. Since it is impossible to know of all possible defects and deviations sources, we learn the deviation from measurement data, leveraging error propagation approaches such as steam of variation. We introduce the term Part Variation Modeling representing the first element of the KCP. The focus lies on the identification of product dimensions caused by machining errors, which according to Huang and Djurdjanovic, is one of the fundamental problem of multi-stage production systems [3, 8].

To understand how variation of deviation and defect occur and propagate in the stream of manufacturing of a piece, a comparable formulation will be derived. This model must allow for describing both, nominal parts taken from e.g., CAD files, and the actual component taken from actual state describing data. Ultimately, comparison of nominal and actual part describing parameters shall provide insight into how each parameter varies down the stream taking into account unknown sources of errors. Additionally, we may use the parametric

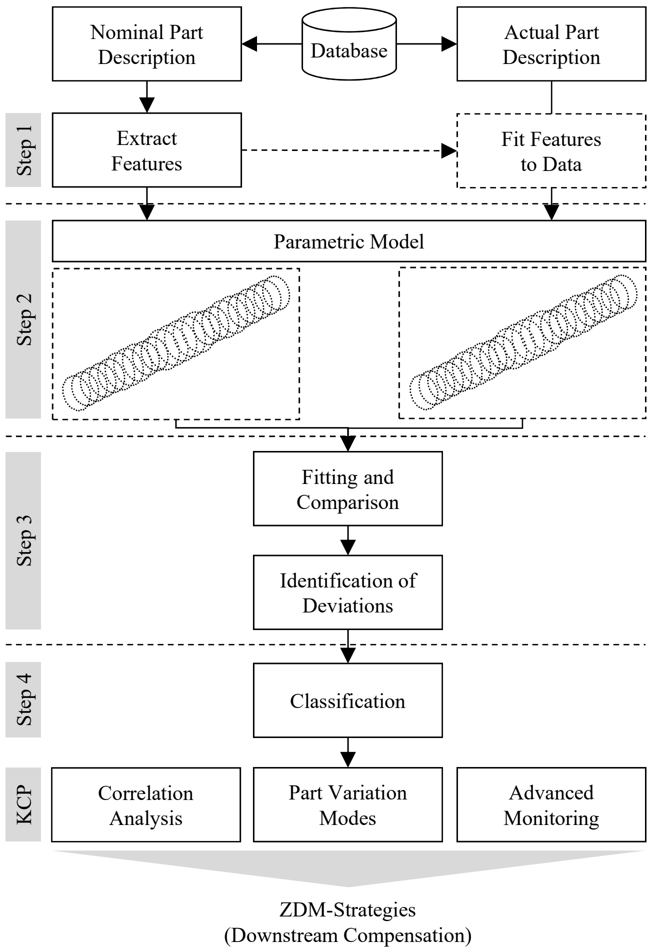

Fig. 2. Concept of PVM for the identification of deviations within multi-stage production systems for reaching ZDM.

model to also observe a single stage's quality of production over time and predict imminent failure.

A. Concept of the Approach

Our approach shown in Figure 2 focuses on detecting dimensional deviations between nominal state and actual state of the manufactured part within each process step. Knowing a part's deviations, different production strategies can be applied to compensate for errors. At first, all sources describing the nominal part geometry are collected. Next to CAD models for each process state, additional information about manufacturing tolerances from technical drawings are used to describe the acceptable deviations between the nominal product design and the part geometry after a manufacturing process. In order to create a basis for comparison with the actual descriptive data in the following intentions, we implement a parametric model. Due to this, CAD-files, technical drawings and other sources describing the nominal part have to be translated into a common format in order to built up the parametric model (see step 1). Rotating components consist mainly of rotationally symmetrical features like cylinders of cones, but also of asymmetrical ones such as grooves or borings (cf. Figure 3

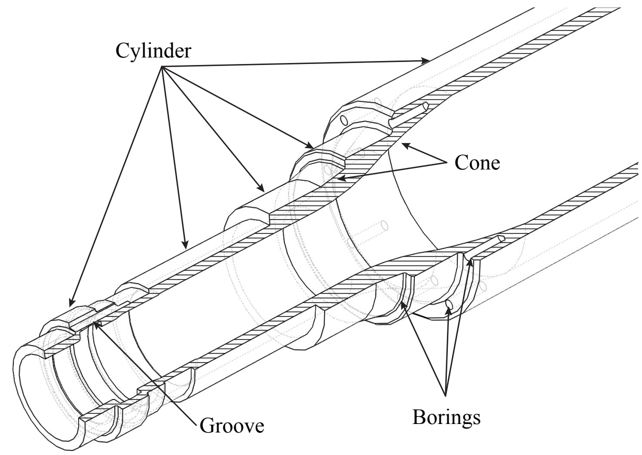

Fig. 3. A turbine shaft in lightweight design as an example of a rotating parts including symmetric and asymmetric features

for an exemplary shaft). PVM determines what features a component can be composed of based on existing geometries.

To correctly determine defects and deviations, quantitative data of both nominal and actual component must be comparable data sets, which we achieve by also applying the parametric model description to our physical component (see step 2). Before starting with the comparison, due to measurement system's inaccuracies or measurement localization problems, both parametric models have to be fitted in each other using different kind of optimization methods. Once a deviation has been identified it is collected in a database. The first possibility of gathering information about defect appearance and propagation will happen during the ramp-up phase. All critical processes are first identified without using compensation strategies in order to initiate the stream of variation within the multi-stage production. This allows the recorded variation along the entire multi-stage production process to be mapped to each component and to search for causes, patterns and propagation of defects. Having this knowledge, part variation modes are defined and used for finding compensation strategies in order to remedy the issue. The identified defects and deviations are classified by their property e.g., diameter deviation (axial) or length deviation (radial) on cylindric features. Knowing the class of deviation, specificities on the extent of each deviation are derived in order to give a more detailed feedback to the control system (cf. Figure 1). In the end, next to extracted knowledge of the correlation analysis and advanced monitoring, part variation modeling gives transparency of part variation along the multi-stage production system and allows development of ZDM strategies.

B. Parametric Model

Let us define a component as collection of n_{k} features with feature-dependent parameters. As such, the component does not have any parametrization itself but its properties can be

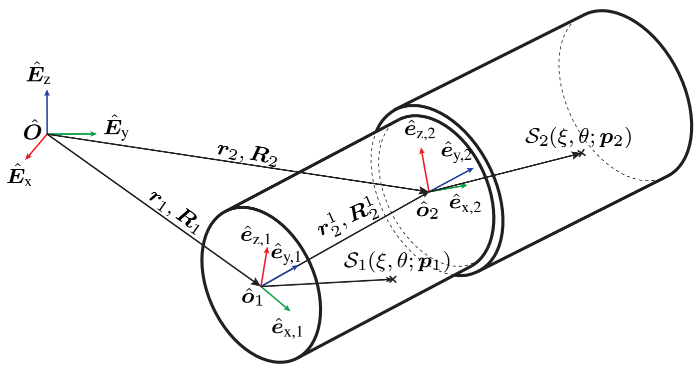

Fig. 4. A 2-feature piece with the absolute and relative positioning of consecutive features as well as with respect to the world frame.

inferred from some or all features. Every component comprises n_{p} parameters, which we combine in the parameter vector tuple $\boldsymbol{p} \in \mathcal{P} \subset \mathbb{R}_+^{n_{\mathrm{p}}}$. The parameter space $\mathcal{P}$ is chosen to be a subset of $\mathbb{R}_+^{n_{\mathrm{p}}}$ for we allow some parameters to only be integer valued while others may be irrational numbers. However, for reason of plausability, we choose all parameters to be of positive values only.

First, we define a local coordinate system of feature k denoted $\mathbb{E}_k := \{\boldsymbol{o}; \hat{\boldsymbol{e}}_{\mathrm{x},k}, \hat{\boldsymbol{e}}_{\mathrm{y},k}, \hat{\boldsymbol{e}}_{\mathrm{z},k}\}$ (cf. Figure 4). Without loss of generality, we require $\hat{\boldsymbol{e}}_{\mathrm{z},k}$ to be collinear with the feature's axis of rotation, consequently $\hat{\boldsymbol{e}}_{\mathrm{x},k}$ and $\hat{\boldsymbol{e}}_{\mathrm{y},k}$ follow from the right-hand rule and may be chosen by liking. A volumetric description of the feature in 3 dimensions is then given by the operator $\mathcal{S}_k(\xi, \theta; \boldsymbol{p}_k)$ as function of normalized axis coordinate $\xi \in \Xi = [0, 1]$, angular coordinate $\theta \in \Theta = [0, 2\,\pi)$, and parameter vector $\boldsymbol{p}_k$ such that

$$\Xi \times \Theta = [0, 1] \times [0, 2\,\pi) \ni (\xi, \theta) \mapsto \mathcal{S}(\xi, \theta; \boldsymbol{p}) \in \mathbb{R}^3 \,. \tag{1}$$

For a simple cylindrical feature, the parameter set $\boldsymbol{p}_{\mathrm{cyl}}$ takes the form $\boldsymbol{p}_{\mathrm{cyl}} = \{r_{\mathrm{cyl}}, l_{\mathrm{cyl}}\}$ where r_{cyl} is the cylinder radius and l_{cyl} is the cylinder length. The operator $\mathcal{S}(\cdot)$ may then be parametrized as

$$\mathcal{S}_{\mathrm{cyl}}(\xi, \theta; \boldsymbol{p}) = \begin{bmatrix} \boldsymbol{p}_1 \, \cos\theta \\ \boldsymbol{p}_1 \, \sin\theta \\ \boldsymbol{p}_2 \, \xi \end{bmatrix} .$$

Our component to-be-modeled is finally composed of n_{k} successive features, each following Equation (1), for which we obtain the combined parameter set $\boldsymbol{p} = \{\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_{n_{\mathrm{k}}}\}$. To describe position and orientation of each feature in world frame $\mathbb{E} := \left\{\hat{\boldsymbol{O}}; \hat{\boldsymbol{E}}_{\mathrm{x}}, \hat{\boldsymbol{E}}_{\mathrm{y}}, \hat{\boldsymbol{E}}_{\mathrm{z}}\right\}$, we use the affine transformation matrix

$$\boldsymbol{T}_k^{k-1} = \begin{bmatrix} \boldsymbol{R}_k^{k-1} & \boldsymbol{r}_k^k \\ \boldsymbol{0}_{1\times 3} & 1 \end{bmatrix} ,$$

in which $\boldsymbol{R}_k$ is the spatial rotation matrix and $\boldsymbol{r}_k$ is the displacement vector. We assume, consecutive features rotated only about their respective $\hat{\boldsymbol{e}}_{\mathrm{z},k}$ axis i.e., $\boldsymbol{R}_k = \boldsymbol{R}_{\mathrm{z}}$ for $k \in [2, n_{\mathrm{k}}]$; only feature $k \equiv 1$ may be rotated about all axes of $\mathbb{E}$. It then follows for the surface of feature k with respect to its preceeding feature $k-1$ as

$$\begin{bmatrix} \mathcal{S}_k^{k-1}(\xi, \theta; \boldsymbol{p}_k) \\ 1 \end{bmatrix} = \boldsymbol{T}_k^{k-1} \begin{bmatrix} \mathcal{S}_k(\xi, \theta; \boldsymbol{p}_k) \\ 1 \end{bmatrix} ,$$

or with respect to world frame $\mathbb{E}$ as

$$\begin{bmatrix} \mathcal{S}_k^{\mathbb{E}}(\xi, \theta; \boldsymbol{p}_k) \\ 1 \end{bmatrix} = \left(\prod_{l=1}^{k} \boldsymbol{T}_l^{l-1} \right) \cdot \begin{bmatrix} \mathcal{S}_k(\xi, \theta; \boldsymbol{p}_k) \\ 1 \end{bmatrix} .$$

If we additionally allow feature k to be shifted with respect to the axis of rotation of feature $k-1$, we obtain the following explicit transformation matrix

$$\boldsymbol{T}_k^{k-1} = \begin{bmatrix} \boldsymbol{R}_{\mathrm{z}} & \boldsymbol{r}_k^{k-1} + \boldsymbol{\Delta}_k^{k-1} \\ \boldsymbol{0}_{1\times 3} & 1 \end{bmatrix} ,$$

in which $\boldsymbol{r}_k^{k-1} = \operatorname{diag}(\hat{\boldsymbol{e}}_{\mathrm{z}}) \cdot \mathcal{S}_{k-1}(\xi = 1, \theta; \boldsymbol{p})$, and $\boldsymbol{\Delta}_k^{k-1}$ is the spatial displacement vector of feature k with respect to feature $k-1$.

The final component given in world frame $\mathbb{E}$ can then be described as sum of all features

$$\mathcal{S}(\xi, \theta; \boldsymbol{p}) = \sum_{k=1}^{n_{\mathrm{k}}} \mathcal{S}_k^{\mathbb{E}}(\xi, \theta; \boldsymbol{p}_k) \,.$$

C. Obtaining Parameter Deviation

As first step to obtaining quantitative values for parameter deviation, we map available sensory data onto the parametric model we defined in the previous section. Assuming a set of measurement data μ_k for feature k, we let the parameters of this feature $\hat{\boldsymbol{p}}_k$ be estimated given

$$\begin{aligned} &\min_{\hat{\boldsymbol{p}}_k} \|\hat{\boldsymbol{p}}_k - \boldsymbol{p}_k\| \\ &\text{s.t. } \|\mathcal{S}_k^{\mathbb{E}}(\xi, \theta; \boldsymbol{p}_k) - \mu_k\| \leq \varepsilon \,, \end{aligned} \tag{2}$$

where $\varepsilon > 0$ is the general tolerance of feature k. Special care must be taken since the measurement data may be given only for discrete values along axis coordinate ξ and surface coordinate θ. To accommodate for this, we define $\hat{\boldsymbol{p}}_k$ to read

$$\hat{\boldsymbol{p}}_k = \boldsymbol{p}_k + \Delta\boldsymbol{p}_k(\xi, \theta) \,,$$

where $\Delta\boldsymbol{p}_k$ is an arbitrary offset function chosen according to the number of measurement points. For example, given a single measurement point along the feature, we define $\Delta\boldsymbol{p}_k := c \equiv \text{const.}$, for two measurement points we define $\Delta\boldsymbol{p}_k := m\,\xi + c$. Ultimately, this definition of the parameter deviation leads to a linear, one-dimensional optimization problem in every of the feature's n_{k} parameters where the objective function is highly non-linear.

Solving the optimization problem Equation (2) gives the parameter set $\hat{\boldsymbol{p}}_k$ which defines the actual feature in the same way the nominal feature is described. Since these data are comparable, a simple arithmetic comparison of every single parameter can be obtained and later on used for classification and categorization into part variation modes.

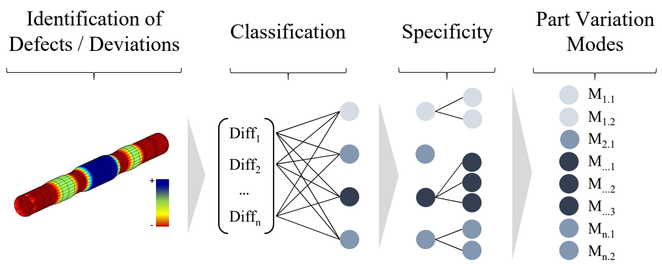

Fig. 5. Development of Part Variation Modes as a result of PVM

D. Part Variation Modes

Figure 5 describes how part variation modes are created. First, deviations are identified by comparing the target and actual state of the component using the parametric models. Based on the identified deviations, self-organizing maps and machine learning are used to create categories that serve to roughly classify the deviations. In order to determine the compensation strategies in a further step, the classification must be subdivided into subcategories. For example, a deviation of a diameter at a specific point can be different. However, it can decide next to other decision points (buffer time, time effort, etc.) if the part has to go to a rough, sensitive or finish drilling process depending on the specificity. It must be clear whether the part can still be corrected or whether it has already exceeded the dimensional requirements of the final part. If this is the case, another product with other specifications is searched in manufacturer's portfolio. Thus scrap can be minimized by manufacture a new part out of the defective. However, if the part can still be repaired, the part variation modes which can be also combined if more than one mode is present, will help to define ZDM strategies.

IV. Conclusions and Outlook

The introduced approach for part variation modeling offers possibilities to determine deviations by comparing nominal part descriptions and measurement data of rotating parts in multi-stage production systems. The aim is to create a preferably general solution to handle multiple input sources especially with regard to data gathered by different sensor systems or manual measurements in every stage of production line. In the course of later application, the development is designed to enable automated processing and increase the transparency with respect to currently unknown influences. Therefore, the work presented uses a feature-based parametric description language in order to depict both, nominal and actual part information. This modeling method is characterized by high flexibility achieved by combining predefined components, e.g. cylinders or cones. Furthermore, the positioning of asymmetrical features is possible, offering broad potentials of design freedom. Subsequently, the nominal and measurement model can be fit and compared by means of optimization strategies and machine learning methods. However, these concepts are currently under development and need to be further worked out and validated. In addition, the generation of part variation modes has to be conducted in the context of the introduced industrial use cases. This includes statistical analysis of gathered deviations during ramp-up phases as well as examination of stream of variations to create suitable control strategies to counteract identified defects within the serial production. Future work also aims, inter alia, at automated conversion from available CAD data to parametric models. Summarizing, the presented work enables the implementation of zero-defect strategies such as downstream compensation methods, derived from knowledge, gained by identified deviations and according defect patterns. These developments should contribute in their entirety to increasing the effectiveness of today's manufacturing systems and improve the associated product quality. In this context, the need for end-of-line repair measures will be reduced, thereby enhancing competitiveness of European manufacturing industry.

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