

## A control model for downstream compensation strategy in multi-stage manufacturing systems of complex parts

Maria Chiara Magnanini\*, Florian Eger\*\*, Colin Reiff\*\*,  
Marcello Colledani\*, Alexander Verl\*\*

\*Dipartimento di Meccanica, Politecnico di Milano, Milano, Italy (e-mail: [mariachiara.magnanini@polimi.it](mailto:mariachiara.magnanini@polimi.it), [marcello.colledani@polimi.it](mailto:marcello.colledani@polimi.it)).

\*\*Institute for Control Engineering of Machine Tools and Manufacturing Units ISW, University of Stuttgart, Stuttgart, Germany, (e-mail: [florian.eger@isw.uni-stuttgart.de](mailto:florian.eger@isw.uni-stuttgart.de), [colin.reiff@isw.uni-stuttgart.de](mailto:colin.reiff@isw.uni-stuttgart.de), [alexander.verl@isw.uni-stuttgart.de](mailto:alexander.verl@isw.uni-stuttgart.de))

**Abstract:** The capability of delivering high-quality products with the required service level is a key factor for competitiveness in manufacturing companies. Zero-Defect Manufacturing control strategies aim at ensuring these targets grounding on the combination of knowledge extraction from the process and advanced statistical tools. This work presents the approach proposed within the EU-funded project ForZDM for selected use-cases in different industrial sectors characterized by multi-stage manufacturing systems and high-value complex parts. The control model is proposed and the overall control strategy is presented with respect to the state-of-the-art solutions, in order to show a comprehensive methodology integrating the joint product-system quality-oriented approach.

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**Keywords:** Zero-defect manufacturing; Downstream compensation; Adaptive control; Part variation modeling; Multi-stage manufacturing systems.

### 1. INTRODUCTION

Multi-stage manufacturing systems where parts are characterized at the same time by high quality requirements and complex features such as train axles or airplane turbine shafts to be processed represent a challenging industrial context. In fact, manufacturing companies are pushed to deliver high-quality products with the required service level if they want to remain competitive on the market. Therefore, the quality strategy assumes a relevant role with respect to the overall production strategy. End-of-line quality checks represent the gate through which customers' requirements must be satisfied, in terms of quality, safety and functionality. However, the final product is only the result of multiple stages affecting the overall quality. Along the process chain, defects are generated by different operations in different stages, and the capability of detecting them, or detecting the possibility to generate a defective product, can be easily translated in time and cost savings. In fact, a late identification of process deviations or product defects leads to ex post compensation strategies, that aim at fixing the quality with an unnecessarily additional amount of time, material, resources and energy. As a consequence, both researchers and practitioners focused on methodologies capable of addressing this issue by providing approaches that increase the quality of product and the process capability. More traditional approaches address separately the product quality and the process capability, but recently new paradigms show the importance of considering these aspects as integrated (Colledani, 2014). Among these, Zero-Defect Manufacturing approach aims at reducing the defective parts by implementing integrated strategy capable of identifying the defect as soon as possible, in order to avoid the propagation of defect along the process chain, minimize the scrap production and reduce the impact of eventual rework.

Indeed, the development of integrated product-system quality-oriented strategies becomes an opportunity for increasing the company reactivity to the customer requirements and therefore its competitiveness on the market. In order to do so, being aware of both technological and organizational complexity of manufacturing systems is essential. Increasing complexity of multi-stage manufacturing 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 (Fong, 1998). Stream of Variation (SoV) theory integrates control theory for design and control purposes with multivariate statistics for error diagnosis and prediction (Huang, 2000 and Djurdjanovic, 2001). In multi-stage manufacturing systems each stage is by itself a source of variability that contributes at the determination of the quality in the final part (Abellan-Nebot, 2012). Being aware of variability helps more than using optimal control strategies that do not take it into account (Djurdjanovic, 2017), therefore a suitable and implementable control strategy for defect reduction in multi-stage manufacturing systems should consider from the beginning the impact of the variability from multiple sources. One of the major challenge becomes the characterization of controllable and uncontrollable sources of variability with respect to the quality of the final part. In this framework, the information gathering process become relevant. Indeed, 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 (Wang, 2013). ZDM-oriented strategies aim at quality improvement of both, product and process grounding on state-of-the-art methodologies. These methodologies establish prediction of deviations from mathematical models in order to define

optimal forward-strategies for improving key product characteristics (Shi, 2009). In fact, compensation strategies (Djurdjanovic, 2005), adjustment procedures (Frey, 2001), and inspection strategies (Colledani, 2014), are defined for downstream stages to close the loop of quality control (Coupek, 2017).

The remain of the paper is organized as follows: the approach of the ForZDM project is pictured in Section 2; in Section 3 the industrial use-cases where the methodology is going to be implemented are described; then, the control model is presented in Section 4; the related approach for the downstream compensation is introduced in Section 5; in Section 6 the main contributions and challenges for future works conclude the work.

## 2. THE FORZDM APPROACH

The goal of the ForZDM project is the development, implementation and demonstration of next generation ZDM strategies capable of dynamically achieving production control solutions for multi-stage manufacturing systems (Eger, 2018a). The ForZDM project, funded by the European Union as part of the Horizon 2020 cluster, deals with use-cases coming from high-value complex-part production, i.e. jet engines shafts, medical micro-catheters, and railway axles. The idea of the zero-defect manufacturing aims to eliminate scrap and rework by analyzing and optimizing multi-stage production systems through data-driven and learning-based approaches from a holistic point of view. Within the international project, a generic architecture is to be developed that covers the entire spectrum of a global zero-defect manufacturing system, from sensor development, via centralized data acquisition, data analysis using statistical methods and artificial intelligence, to proactive control interventions in the actual manufacturing process.

In the past, the focus was on the optimization of individual and separate processes using static process control systems. However, even after the optimization of a single production process, there is still the possibility of defect generation in the form of deviations propagating and superimposing over several process steps. These include, for example, dimensional and geometric variations due to tool wear or inhomogeneity of the raw material. These deviations are often unpredictable and their causes cannot be detected ad hoc, especially if only a limited number of sensor systems and analysis methods are used. These defects are therefore often only detected at the end of a manufacturing process, during quality control. Since the defective product continues to go through its intended production process, such defects are cumulated, which in many cases leads to rejects or enormously high costs due to rework.

A decisive factor for the successful realization of a zero-defect manufacturing is the achievement of the most transparent production possible. Every production line already offers access to data without much effort. In addition to the recording of process variables and machine-related measured values, quality data of the parts must also be recorded. In order to record the quality as completely as possible across the entire

multi-stage system, existing production systems often have to be retrofitted with a large number of sensor systems. It is of enormous importance to be able to assign the measured values to the respective parts. This is achieved, for example, by assigning a unique identification number to each part, which can be captured by QR scanners at each station in the process chain. The extensive data acquisition forms the basis for all other higher-level systems and developments. All data is stored in a database to enable centralized evaluation. However, since the data formats and frequencies vary from sensor to sensor, the data streams must be prepared for processing by decentralized mechanisms.

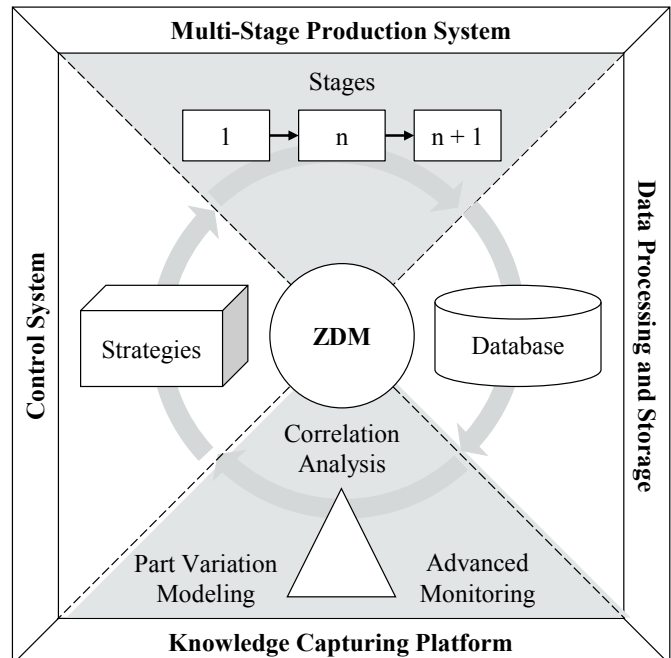


Fig. 1. ForZDM Approach

In order to extract knowledge from the data collected in the central database, the Knowledge Capturing Platform (KCP) is introduced. The platform contains various statistical and analytical tools for processing the data. The data collected via the multi-sensor network and the data management platform represent the most important source of knowledge about the causes of defect generation and their propagation mechanisms along the production line. This knowledge must be extracted and structured in the KCP so that it can be used for all upcoming developments.

The KCP thus forms the interface between the collected data available in the database and the ZDM strategy platform, which defines optimization and defect compensation strategies based on the knowledge of the evaluated data. In order to extract the knowledge from the existing data, suitable data analysis tools (Correlation Analysis, Advanced Monitoring and Part Variation Modeling), as shown in Figure 1, are developed to identify significant modes of dispersion of product quality taking into account interrelations between parameters in different production stages. In addition to correlation analysis, Part Variation Modeling ensures that defects are detected as early as possible by comparing geometric and dimensional set values with data describing the actual state after each process. The causes of defects and

propagation paths can thus be determined efficiently. This allows a predictive adjustment of the influencing process or machine parameters to the transient conditions that lead to defects. Two types of mechanisms will be used to characterize these complex relationships: top-down knowledge-based and bottom-up data-based approaches. This means that the data generated by the multi-sensor system at the production line are transferred hierarchically upwards (bottom-up) via the database to the KCP. By using data-driven methods, knowledge is extracted from the data, which in turn is used to optimize the multi-stage production system on a knowledge basis (top-down).

Based on the results of the KCP, strategies for achieving an almost faultless production are derived. This includes strategies for defect avoidance on the one hand and strategies for eliminating errors that have already occurred on the other. However, the consideration of stochastic defects cannot be guaranteed. For this reason, downstream compensation strategies are necessary in order to eliminate errors whose occurrence could not be prevented. The first important step is the earliest possible identification of the deviation and thus the definition of possible measures for compensation or at least reduction of the effects of the defect. The primary goal is to adapt the regular subsequent process steps that affect the characteristics of the defect. In addition, it may also be necessary to redefine the entire process chain and change the sequence of the individual process steps. In addition, the adaptation of the planned nominal geometry can be taken into account. This makes it possible to manufacture a further component, e.g. with smaller dimensions, so that the defect that has occurred can be completely eliminated. This enables the production of parts for a different order and thus the reduction of rejects as well as cost- and time-intensive reworking.

### 3. DESCRIPTION OF THE SYSTEM

In this paper, the multi-stage manufacturing process of a turbine shaft is used as an example to explain the approach of downstream compensation in a practical environment. However, fundamental details of the production plan and the list of operations performed cannot be shared for confidential reasons. Due to this, Figure 2 presents a simplified and generic manufacturing system which shows an extract of the production for rotating parts.

Each operation is performed on a CNC machine and may or may not require operator supervision. Along the process chain, different measurement procedures are used to check the quality of the dimensional and geometrical characteristics. However, not all characteristics of a part can be measured within a production process. This can result in possible undetected deviations of the part, which can lead to problems during further processing or to rejects at the end of production. Already machined surfaces serve as reference for the following machining steps, which in case of a defective reference causes a accumulation of deviations. To avoid this, early defect detection is indispensable in today's production systems.

Not to be noticed in Figure 2, but nevertheless part of the formation process of a turbine shaft, is the fact that a raw material has to be brought to a semi-finished product. In an iterative process, the component is alternately heated and forged until it has an almost cylindrical shape. The first machining process, rough turning, generates the semi-finished product, which is characterized by a high degree of variability in terms of both geometric and dimensional properties.

For reasons of weight, both on turbine shafts and on shafts for trains require a bore in the centre. For shafts of up to three meters in length, a complex tool is required for machining the bore. Deviations due to high stress leading to vibrations cannot be avoided. These deviations become visible during the End of Line control, the balancing stage, at the latest. However, it is then too late to rework the part. To avoid this, a measurement of the inner contour which outputs a point cloud serves for the calculation of the new references. These are necessary for the clamping of the part for the machining of the outer contour in order to have a perfect outer contour without unbalance at the end of the line.

The paper presents a research approach to solve this problem with the capabilities of a multi-stage complex manufacturing system. The measurements of the balancing stage as well as disturbance variables along the entire process are taken into account. The aim is to develop a control system that can compensate for dimensional deviations in the component, taking into account the variations that the component is subject to along the process chain.

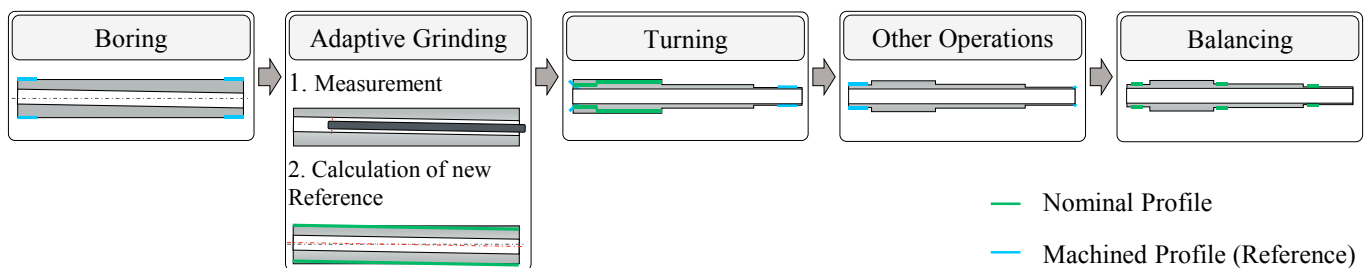


Fig. 2. Simplified Multi-stage Manufacturing System for the ForZDM use-cases.

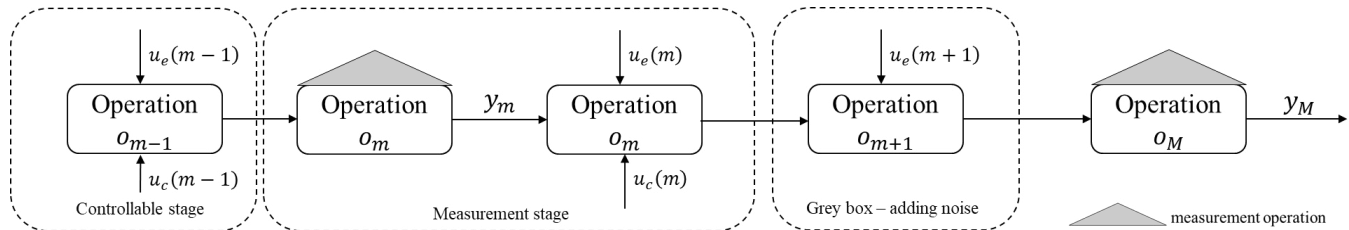


Fig. 3. Control model proposed of the multi-stage manufacturing system.

#### 4. THE CONTROL MODEL

In the following, the control model for the multi-stage manufacturing system described in Section 3 is proposed. The control model will then be integrated with the Part Variation Model defined in (Eger, 2019) for the overall control strategy. There, the part is defined as a sum of features  $S(\xi, \theta, p)$  where  $\xi$  and  $\theta$  represent respectively the normalized axis coordinates and angular coordinates, and  $p$  represents the vector of parameters describing the features. The proposed control model links the product features to the multi-stage manufacturing process. It links the uncertainty accumulating on the part through the multi-stage process in order to identify the suitable control action. Moreover, as it will be explained in Section 5, it aims at combining a local control with a system-level control.

##### 4.1 Modelling Assumptions and Notation

As shown in Figure 3, the system is composed by  $m = 1 \dots M$  machines, which include process machines and measurement machines. Each machine can perform  $o_m = 1 \dots O_m$  operations. Each machine  $m$  introduces a variability on the part based on the clamping system with distribution characterized by mean  $\mu_m$  and variance  $\sigma_m$ . Each operation  $o_m$  introduces some deviation on the part with distribution characterized by mean  $\mu_{o_m}$  and variance  $\sigma_{o_m}$  on part features. The decisional variables are represented by the position of the clamping system  $u$ . If the clamping system in operation  $o_m$  can be adapted, we define a controllable variable  $u_c(m)$ . If the clamping system in operation  $o_m$  cannot be adapted, we define an uncontrollable variable  $u_e(m)$ .

For each measurement machine, a vector of measurements errors  $y_m$  is obtained with respect to the nominal part, where each entry of the vector corresponds to a measured feature within stage  $m$ . The vector of measurements  $y_M$  describes the errors in the final actual part with respect to the nominal part. Each operation might add a noise characterized by mean  $\xi_m$  and variance  $\sigma_{\xi_m}$ . Each operation might add a noise characterized by mean  $\zeta_{o_m}$  and variance  $\sigma_{\zeta_m}$ .

##### 4.2 Relation with the Part Variation Model (PVM)

The relation between the PVM model and the proposed control model is given by the vector of measurements  $y_m$ . In fact, the vector of measurements  $y_m$  is defined grounding on the PVM as follows:

$$y_m = \hat{p}_{k(m)} - p_k$$

Where the index  $k(m)$  represents a subset of features  $\hat{p}_k$  that can be measured within stage  $m$ . In fact, the PVM describes

the relations among features that are worked in different stages, since it describes the part by the sum of all its features. Therefore, the control model takes into account how the features are processed along the multi-stage manufacturing system, whereas the PVM describes the relations among the measured features.

##### 4.3 Model structure

The model links the measurement vectors to the controllable and uncontrollable variables. Each variable contributes to the measured deviations in  $y_m$ . The state-based model has the following form:

$$\begin{aligned} x(m) &= A_m \cdot x(m-1) + B_{c_m} \cdot u_c(m) + B_{e_m} \cdot u_e(m) + \zeta_{o_m} \\ y(m) &= C_m \cdot x(m) + \xi_m \end{aligned}$$

Where  $A_m$  is the matrix describing how errors accumulated up to and including operation  $o_{m-1}$  are transformed and influence errors in operation  $o_m$ ,  $B_{c_m}$  and  $B_{e_m}$  describe how new errors are introduced into the work piece at operation  $o_m$  and  $C_m$  connects errors of the nominal parameters  $x(m)$  to the measured errors  $y(m)$ . Specifically, matrix  $C_m$  describes how the datum quotation might be different in the considered stage with respect to the nominal quotation. In fact, the coordinates of a measured feature in a specific stage are subjected to eventual deviations on the reference points that may be added in further stages. Therefore,  $C_m$  includes the mapping from the local reference system in stage  $m$  to the nominal reference system on the final part.

These matrices are obtained from real data using the correlation analysis tool described in (Eger, 2018b) and from physical principles as described in the Part Variation model proposed in (Eger, 2019).

Mathematical manipulation (see for instance Djurdjanovic (2001)) leads to the following input-output relation:

$$y_m = T_{c_m} * u_c(m) + T_{e_m} * u_{e_{o_m}}(m) + \Xi_m$$

Where  $T_{c_m}$  describes how controllable variables  $u_c$  affect the measured features in operation  $o(m)$  and  $T_{e_m}$  describes how uncontrollable variables  $u_e(m)$  affect the measured features in operation  $o(m)$ , and  $\Xi_m$  represents the summed uncertainty added in each operation and machine.

The presented control model grounds on the Knowledge Capturing Platform that characterizes the ForZDM approach, as illustrated in Section 2. Indeed, the goal of the control model is also to provide a structured formalization of the knowledge that is needed to control the multi-stage manufacturing system.



In the long term, the gathered data from the process can improve the control model in order to reduce not only the uncertainty of the existing noise coming from the process, but also to increase the confidence of the model parameters.

### 5. OVERVIEW OF THE STRATEGY

The proposed approach aims at developing a control strategy that can compensate for dimensional deviations in the component, by taking into account the variations that the component is subject to along the process chain, which is represented by the control model, and how the deviations in the measured features may affect each other, which is represented by the PVM.

As explained in Section 3, not all stages can be controllable due to process requirements, contract issues with customers, technological constraints on machines. Moreover, not only at each stage only some features are measured, but the measured features might be not explicitly related to the next process stage, in the sense that in stage  $m$  an internal diameter might be measured, but in stage  $m + 1$  an external feature can be machined. Indeed, the two features affect each other, which is why a PVM is needed. On the other hand, the link between stages is necessary for the development of an integrated product-system control strategy, which is why the control model has been developed.

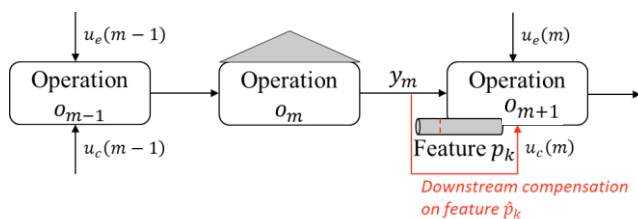


Fig. 4. Control strategy for the downstream compensation.

Therefore, the control model will be used within a downstream compensation strategy, where at each controllable stage, the information obtained from the last measurement stage will be used to compensate the deviations taking into account the noise in the control introduced by the further stages.

### 6. CONCLUSION: CHALLENGES AND NEXT STEPS

This paper presents a control model aiming at the downstream compensation for multi-stage manufacturing systems characterized by machining operations of complex parts. The control strategy has been framed within the ZDM approach and the detailed solution has been described. The EU-funded project ForZDM is exploiting the proposed solution in two use-cases from high-value manufacturing sectors where the core process is represented by multi-stage machining operations. However, when dealing with multi-stage manufacturing systems of complex parts, the implementation in real environment of such system-level strategies might not be easy for various reasons. First, gathering the correct and useful data to build the Part Variation Model and to validate it takes time and effort; second, a sudden implementation in a

real company of a model-based control strategy requires a full commitment from the production management that is usually not eager to change the production strategy. Hence, the first step for an implementation in a real industrial environment of a model-based control strategy can be expected to be at local level, i.e. on the critical stage, and then be enlarged to a system level.

On the other hand, from the methodological viewpoint the challenges are manifold as well: first, the selected products do have complex asymmetrical features requiring the Part Variation Modelling to be extremely flexible; second, the use-cases are characterized by multi-stage processes consisting of different operations whose parameters cannot all be adapted due to process requirements; finally, there are many variability sources along the process that do have a high impact on the quality of the final products.

In this work, the combination of knowledge-based methods and advanced analytics combined with statistical tools provides the right enablers for a useful and implementable ZDM-oriented control strategy. Then, the next steps include the validation of the model on the real manufacturing system and the development of an optimal control strategy. Therefore, future activities are devoted to the implementation in real context and implementing issues are going to be addressed, such as the robustness of the proposed method to the uncertainty of the input data. Moreover, being able to implement such model paves the way for focusing on other system-level industrial questions, as the improvement of the sensor allocation along the multi-stage manufacturing system and the responsiveness of the control strategy to the process deviations.

It is worth mentioning that the proposed control model does not address the control optimality yet. Indeed, in order to be implementable an optimal control strategy should be robust not only to the uncertainty of the input data, but also to the uncertainty of the model parameters. In fact, an optimal control strategy that does not consider the uncertainty of the model itself might lead to wrong, if not counterproductive, control decisions. Therefore, a necessary step before the development of an optimal control strategy is represented by the analysis of the impact of the model uncertainty on the identified quality performance measures.

### ACKNOWLEDGEMENTS

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 723698. This paper reflects only the author’s views and the Commission is not responsible for any use that may be made of the information contained therein.

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