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Zero defect manufacturing strategies for reduction of scrap and inspection effort in multi-stage production systems

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Abstract

Multi-stage production systems offer a huge potential for defect compensation and defect propagation avoidance on system level, in contrast to current single-stage solutions, in order to reduce scrap and to minimize time-consuming and cost-intensive quality control. Integration of additional sensor systems and sophisticated analysis of the acquired signals enable strategies in the field of downstream compensation, inline rework and enhanced process control without including additional process and inspection stages. The presented strategies are validated in three emerging European industrial sectors (aerospace, railway and medical) yielding a universal solution for zero defect manufacturing in multi-stage production systems.

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Keywords: Zero-defect manufacturing; Effect elimination; Multi-stage; Production system

1. Introduction

Increasing volatility in the global and local economies, shortening product life cycles and increasing degree of product customization call for production systems that comply with these changing demands in all their basic functions, including quality and production control. Current Zero Defect Manufacturing (ZDM) approaches are local solutions focused on single production stages. They are also static and sequential, in the sense that when a problem is analyzed and solved at a specific stage, the company considers the process as ‘frozen’ and moves the attention to a new critical stage. This sequential strategy prevents the company from quickly adapting its production operations to changing production targets, thus undermining its competitiveness on the global market. In order to achieve this, the goal is to develop ZDM strategies that reduce the generation of scrap parts and prevent defect propagation in multi-stage production systems.

End-of-line quality testing is usually applied to assess the product functionality at the end of the process chain [1]. However, this approach does not support the in-line prevention and correction of defects. Emerging Key Enabling Technologies (KETs), such as in-line data gathering solutions, data storage and communication standards, data analytics tools and digital manufacturing technologies offer new opportunities for ZDM. These technologies are increasingly becoming integral part of modern production systems [2]. If these technologies are properly integrated with a cross-KETs approach, new cyber-physical systems (CPSs) can be designed and implemented at shop floor level, to support systemic ZDM solutions [2,3]. CPSs are usually defined as systems integrating computation and physical actuation capabilities [4]. In CPSs, embedded computers and networks

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monitor and control physical processes, usually with feedback loops, where physical processes affect computations and vice versa. The economic and social potential of CPSs is vastly greater than what has been realized yet, and major investments are being made worldwide to develop these solutions in response to emerging industrial problems (Industry 4.0) [5]. This potential in connectivity and computational power in manufacturing can be exploited to support the implementation of efficient in-line quality-oriented production solutions.

Successful projects in the 4ZDM cluster supported by the European Union such as MUPROD, IFACOM [6], MEGAFIT and MIDEMMA demonstrate how to achieve near zero defect level in different manufacturing systems. The focus was to reduce the number of defects in manufacturing of complex high-precision and high value parts by in-line measurement, process control, or enhanced quality control. In MUPROD, an innovative quality control system was developed on lab scale for in-process multi-stage defect reduction [7–9]. MEGAFIT and MIDEMMA were focused on micro-manufacturing processes, including multi-stage micro forming [10–12].

The new research project ForZDM within the 4ZDM cluster aims at developing and demonstrating a next generation ZDM strategy capable of dynamically achieving the production and quality targets grounding on an integrated quality and production control solution for multi-stage systems. In both large volume and small batch production contexts, this solution will allow companies to rapidly deploy a cost-effective line monitoring and control system that will reduce expensive off-line measure-rework-assess loops and avoid the delivery of defective items at the end of the line. The ultimate goal is to reduce the system operational costs and materials wasted in scraps, thus increasing the competitiveness and sustainability of European companies in the global market.

This paper is structured as follows. Section 2 introduces the overall ZDM solution concept and the reference architecture. Section 3 outlines the different data gathering systems while section 4 investigates online defect prevention and defect propagation mitigation solutions. The focus in section 5 lies on system-level ZDM solutions followed by section 6, which highlights the integration in production and equipment control systems. In section 7, the validation in industrial production systems is presented. Finally, a conclusion and outlook is given in section 8.

2. Zero defect manufacturing solution for high value adding multi-stage manufacturing systems

The multi-stage ZDM solution proposed is developed on three different production lines, namely, for jet engine shafts, medical microcatheters and railway axles. These lines provide a basis to deploy the specific contents of the solution and serve as pilot cases to demonstrate the applicability of the solution to very different multi-stage lines.

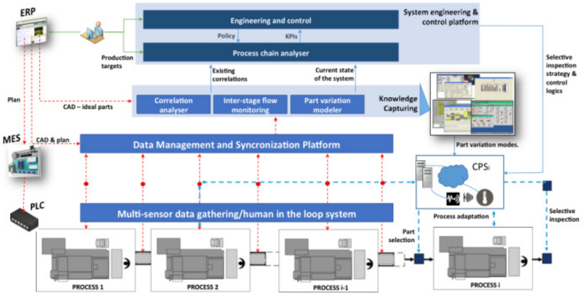

Fig. 1. Reference architecture of the ForZDM solution.

2.1. Zero defect manufacturing system architecture

The reference architecture for multi-stage systems on which the solution proposed by ForZDM is based is represented in Figure 1. The proposed architecture grounds on five major pillars, which are described in the following. The first pillar consists in a comprehensive *Data Acquisition System*, able to collect and synchronize data gathered from different, heterogeneous, multi-resolution and multi-scale data sources distributed in the production line. These data include (i) workpiece quality data, gathered by inspection technologies, (ii) process data, gathered from in-process sensors, (iii) machine state data, gathered by the production monitoring system, (iv) product flow related data, gathered by tracking solutions, and (v) codified feedback, gathered by production line operators. This new integrated data-acquisition system will feed a *Data Management Platform* that will store and update the acquired data in a structured and formalized way. This platform will be enriched with data management, extraction and aggregation features in order to support the knowledge-based analysis of the relevant inter-stage correlations. Overall, this solution will make it possible to achieve observability of the product, process and resource states, throughout the system stages. Connected to the aforementioned data management platform, a suite of *Data Correlation, Error Budgeting and Root Cause Analysis* tools, based on advanced data analytics and artificial intelligence techniques, is included to characterize the significant defect correlations among product, process and resource data, at different stages. This tool will be supported by an HMI to allow the user to model existing correlations via "knowledge-based" and "learning-based" methods.

At zero defect generation level, Cyber Physical Systems (CPS) make it possible to proactively adjust the process parameters, the fixture, and the reference locators before each critical process stage. The information about the incoming part history in the previous stages is used to issue alarms on the specific variation mode of the part, before the process. With these inputs, a model-based approach is used to adjust the controllable variables at the next correlated stage to avoid the generation of defects while processing the part under the identified variation mode. To reduce complexity, a pre-defined discrete set of alternative process parameter sets will be designed and validated for each part variation mode combination. After the processing, if one or more product key quality characteristics is outside the specification limits imposed by design, defect propagation avoidance policies will be triggered. They mainly consist in CPSs for correcting the defect before it reaches the final manufacturing stage in the process-chain. Solutions include (i) workpiece in-line rework, (ii) or workpiece in-line repair through feed-forward adjustments and selective assembly at correlated downstream stages. The selection of the most suitable selective inspections, part flow control, and defect correction policies is based on the analysis of the impact of the action on the overall economic, production logistics and quality performance of the entire process-chain, thus properly managing the trade-off between quality and productivity, at system level. This comprehensive system modeling layer will be continuously fed with shop-floor data, in order to provide a high-fidelity virtual representation of the production flow. Both long-term performance such as the effective throughput, and short-term performance, such as the lot completion time and the service level, will be calculated. This model will be integrated with a suitable search algorithm to optimize the local policies in order to achieve a globally optimum system behavior. A simplified HMI supports production managers to quickly adapt production targets and line management strategies to the specific changing demand levels and features. Moreover, at shop floor level, a distributed monitoring, alarm triggering, and CPS-based control system is included, based on the IEC61499 standard, enabling to implement the quality and logistics strategies optimized at system level. All in all, this systematic and systemic quality and logistics control strategy will represent a breakthrough solution for implementing the ZDM paradigm in complex multi-stage manufacturing systems, grounding on multi-scale modeling, CPSs, big data and data analytics as key enabling technologies. The key components of the proposed architecture are discussed in the following together with the main features of the ForZDM industrial demonstrators.

3. Online data gathering systems

The complexity of multi-stage production scenarios and the adaptive behavior of the proposed ZDM strategies make it necessary to implement advanced features at data gathering layer: automatic device discovering, configuration of sensors, data fusion, filtering strategies and management of operator'sinputs.

3.1. Sensor integration and analysis

To overcome the configuration and discovering challenges, we propose an Internet of Things (IoT) based automatic sensor discovering and configuration mechanism [13] for quick sensor network deployment and reconfiguration. This IoT standard based approach is flexible enough to handle production plant reconfigurations or new sensor placement and enhance the monitoring and defect characterization of the production process. The gathered information is composed of sensor information and operator feedback in different stages of the process. Sensor vastness, heterogeneity and huge data streams make the information access, gathering and processing an active research field [14–16]. User feedback handling and knowledge extraction is critical for defect characterization and correlation: many processes are semi-automatic with a decisive intervention of the operator. Those fundamental challenges of the data gathering collection and processing will be addressed in three fields:

1) Heterogeneous data collection mechanisms: ZDM does not only include sensor data, but also data from production planning systems (ERP), relational databases or defect management systems. The data gathering layer receives and retrieves data from multiple sources, and sends it in a unified format to the data integration and management platform [14].

2) Sensor data fusion: A multi-sensor data fusion model is proposed to provide more robust and uncertain information from the sensors placed in the production. The inherent imperfection of the data and the limitations of the different types or sensors are tackled using KF/EKF techniques [17] to obtain processed sensor data combining different sources.

3) Human feedback processing: The feedback information can be divided in two main categories: structured data (categorized and contextualized information) and unstructured data (free text or comments). Data extraction mechanisms [18] are applied in data gathering layer to properly extract the underlying knowledge.

3.2. Data integration and management platform

Within ForZDM, the software solution OneBase is used as starting point for a data integration and management platform. In the context of the ANSI ISA 95 layer model [19], the OneBase framework offers communication between components of the different layers. This includes devices typically found in manufacturing environments such as PLCs, machines, tools, and various measuring, sensing, inspection and laboratory equipment, manufacturing execution systems (MES) and ERP. The framework is based on a modular and distributed architecture and focuses on fast communication. Its data model is based on data objects called tags, which can be simple (integer, float, string) or complex data types of nested structures. Shop floor objects such as machines or other plant devices are mapped to tags and linked to each other logically. Tag communication relies on a publish/subscribe mechanism, clients can subscribe tags. If a client publishes a change to a tag, all other subscribers will receive a push notification. APIs in object oriented programming languages are available to provide access to tags, so complex logics for shop floor control can be created.

4. Online defect prevention and defect propagation mitigation solutions

Data gathered through the multi-sensor network and data platform represent a new and relevant source of knowledge on causes behind the defects generation and their propagation mechanisms along the production lines. This knowledge has to be extracted and structured in order to take advantage of it for all the upcoming developments.

4.1. Data correlation and root cause analysis

Based on the acquired data, conventional quality control and root cause analysis tools can help to confirm original assumptions or point out line variables not considered up to date and requiring attention. Further information can also be extracted through statistical analysis techniques. But the most useful contribution of the heterogeneous and synchronized collection of line data acquired is the opportunity to identify correlations between defects and variables from different stages, as demonstrated by the MUPROD project and other previous works [20,21]. This provides a basis to model the defects propagation patterns through statistical and machine learning clustering [21,22,22,23].

It is intended that the outcomes from the data analysis are materialized by: (i) eliminating redundant data for agile management and flow of the line information and lean implementation of the data-driven models (ex. defect propagation, CPS), (ii) extending the analysis capabilities to future scenarios by means of GUIs which provide in-plant analysis capabilities to operators and production managers.

4.2. Process control

Control strategies are to be applied on the lines critical processes to avoid the generation or propagation of defects. At the setup phase numerical process models will simulate the process in order to adjust the operation conditions which maintain the process controlled (e.g. cutting forces, generated chip, process temperature) and therefore away from defects. In this sense, the challenges to face rely on implementing and adjusting process models which currently are either inexistent (e.g. the interaction of the cutting tool with coolant and chip in shafts bottle boring) or subjected to much improvement (e.g. microtubes extrusion). Concerning the production phase, critical processes still require control in order to ensure performance within the established conditions and alert on deviations from them which make a defect likely to appear. This control capability is going to be provided by means of monitoring systems. The selection of commercial catalogue systems will ensure the use of mature sensing technologies (e.g. force, vibration, acoustic emission) and robust and reliable electronics for signal processing and analysis and machine interfacing. Nevertheless, sensor signals still need to be analyzed to extract meaningful information and automatic decision making algorithms based on the signals information must be implemented. A specific solution must be developed for each single critical process considered. This is expected to be achieved through multiple signal analysis and machine learning techniques proposed for the purpose [24–26].

4.3. Quality oriented assembly

Quality oriented assembly focuses on a subset of defect compensation strategies that involve selective and adaptive assembly strategies relying on product variation propagation models. This approach integrates analytical and artificial intelligence-based algorithms for compensating part defects by optimizing the assembly strategies.

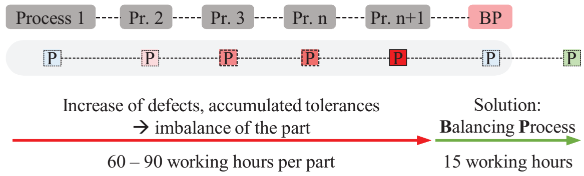

Fig. 2. Simplified multi stage production system for rotating parts with subsequent balancing process.

It must be implemented in a dedicated operational module that is integrated as a decision support kernel, interacting with the physical system by modifying the specific assembly strategy based on the incoming part measurement.

In previous work of the authors, selective assembly strategies were developed for the multi-stage production system of electric motors in the automotive industry [9,27]. A specific artificial neuronal network, namely self-organizing maps, is used for unsupervised defect classification in the production line. Then, a fuzzy inference system selects the optimal combination of conforming parts from the classified sub-sets. This selective assembly approach decreases the amount of scrap parts in early process stages and reduces the scrap rate at the end-of-line quality control to zero. At the same time, the uniformity of the magnetic field of the rotor increases. However, this approach is adapted to one specific use case. In ForZDM, a generic control strategy is developed, that is able to adapt to a priori unknown set-ups of the multi-stage production systems.

4.4. Inline product repair and downstream compensation

Inline rework focuses on a set of technically feasible defect compensation policies, which can be applied after the occurrence of defects within the same process [8]. In contrast to offline repair, no additional operator or working station is needed. Instead, the workpiece remains clamped and is reworked in the same station. The final selection among available technically feasible rework strategies has to be done by verifying quality and logistics performance at system level.

Methods for downstream compensation have already been applied successfully in MUPROD. The goal was to compensate deviations in the magnetic field of single rotor stacks by adaptation of the downstream assembly parameters [27,28]. This approach will be transferred to ForZDM to avoid imbalance propagation in multi stage production systems for high-performance rotating parts (Fig. 2).

The state of the art in this manufacturing sector is to balance the part as quality control in a separate stage after the actual manufacturing process. Each process step can cause small imbalance of the work piece - the result is an accumulation of imbalance.

In this case, downstream compensation, will be applied as feed forward control (Fig. 3). This means: if a defect occurs at an early process stage, the defect can be repaired in a following (downstream) process step. So there is no defect accumulation due to early defect detection while using existing and additional measurement systems this can be e.g. evaluation of motor signals to identify imbalances.

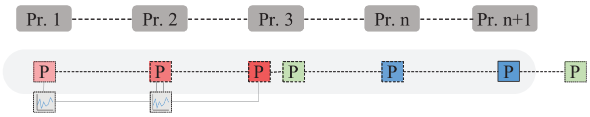

Fig. 3. Production line behaviour under feedforward control.

5. System-level zero defect manufacturing solution

Quality and production control are fundamental functions of modern manufacturing systems that have been traditionally treated by scientists and industrialists almost in isolation. However, recent research and advanced industrial practices showed that quality control strategies have an impact on the system production logistics performance as well as the adopted production control policy has an impact on the critical quality characteristics of parts. A recent CIRP keynote paper [29] well characterized these cause-effect relations, also considering machine degradation and maintenance practices in the overall picture. It also highlighted the need for an integrated approach to jointly optimize, at system level, maintenance, quality and production control strategies, in order to avoid local improvements that can bring minor, or even detrimental, effects at system level. In line with this strategy, the goal of the ForZDM system engineering and control platform is to optimize the joint quality and production logistics control policies to be implemented at shop floor level by integrating quality, production efficiency and economical aspects into a unique framework. This high-level controller analyzes the global coherence and economical feasibility of the decisions taken at local level, and can be used as an effective tool for strategic decision making and "what if?" analysis. This platform will make it possible to optimize the (i) defect propagation mitigation policies, (ii) the part inspection policy and (iii) the part flow and inventory control policies at system level, before the implementation in the real system at shop floor level. In this way, local optimizations that are detrimental at system level will be avoided. The platform will be based on a process-chain modeling and analysis tool [30] that jointly considers the dynamics of the material flow in the system as well as the product variation propagation throughout the process stages, also integrating the relevant correlations between process variables, machine states and product quality characteristics identified with the support of the Data Correlation and Root Cause Analysis tool. Based on the data gathered from the shop floor and available in the Data Management Platform, this tool enables to adapt selective inspection, defect management and part flow control strategies to the specific lot under production, thus optimizing and controlling system operating conditions in order to achieve the desired service level of good quality products also in small batch production contexts.

6. Integration in production and equipment control system

The control system must be distributed, multi-level and allow human-in-the-loop integration, in order to realize the defect avoidance and propagation mitigation logic described in section 4 and 5. The multi-level architecture is divided into three hierarchical tiers: low-level, medium-level and high-level control. Low-level short-term control system utilizes the newly available sensor data gathered from the integrated processing monitoring system (section 3), to control in real-time, a single machine or process. The closed loop controllers obtain their set-points and commands from the medium-level control system or the dedicated HMI for machine operator input. The system is also responsible to transfer relevant information such as machine/workpiece status, alerts and user feedback to higher level controls enabling decision making.

Medium-level medium-term control system is responsible to implement the system-level strategies (section 4) to prevent the generation and propagation of defects. The system includes the distributed control of multiple machines and processes, and autonomous decision making to generate in real-time the set-points and commands for low-level control of a single machine and a comprehensive HMI for the process engineers to visualize execution of control actions (SCADA). It also has an offline component that provides simulation capability, allowing the engineers to confirm in advance the effect of a defect mitigation strategy.

High-level long-term control system performs offline to generate long-term control policies that maximize the production output with minimum defect. It utilizes the system analytics and simulation output (section 5) as well as machine learning to provide the production manager a set of quantified suggestions for process improvement. Decision made at this level is then translated into set-points and commands and sent to medium and low level control systems. Real-time capability is not needed, but may be performed when an order is received from the production MES/ERP system, or via a HMI/SCADA interface accessed by the production manager.

Within the distributed multi-level control system, failures may arise from several components of different manufacturers. In order to cope with this challenge, a detailed failure mode analysis has to be carried out, isolating criticalities and defining an appropriate mitigation strategy. This includes applying safety features like self-testing, monitoring and hardware-based redundancy.

7. Validation in industrial production systems

The ForZDM solution will be customized for and implemented in three different production scenarios; this will make it possible to demonstrate the feasibility of the approaches, methodologies, and technologies developed in the project, and to assess their applicability in a real industrial environment.

Each of the selected end user cases has own specific challenges. For example, in the production of railway axles, the upstream forging process variability has an impact on the downstream machining processes, leading to tool breakages and defective parts. In the production of micro-catheters the variability in the upstream granule material preparation processes (drying, compounding) affects the downstream micro-extrusion process, resulting in geometrical errors. In the production of large jet engine shafts, beside the complexity of machining internal features, the runout compensation strategies implemented in the initial stages have a strong impact on all downstream stages. The ForZDM solution will be progressively deployed in the project's end user cases, in order to validate each module before testing the whole architecture. This approach will allow also to monitor a high number of parameters since the initial phase of the project; in this way, it will be possible to assess the real impact of each implemented policy on the selected production KPIs and to provide quantitative measures of the project impact.

8. Conclusion and prospects

This paper provides a general overview on the ForZDM project approach, with insights on the architecture of the proposed system and the innovative approach proposed for smoothing defects in modern manufacturing industries. By relying on suitable industry 4.0 technologies, the project will demonstrate in different industrial scenarios a novel solution that expands current single process boundaries towards a production line perspective, enabling systemic defect avoidance strategies, tailored on multistage production lines.

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