Human in the Data-driven Zero Defect Manufacturing loop: Case Examples from Manufacturing Companies

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Abstract. Data-driven Zero Defect Manufacturing (ZDM) system gathers and organizes data from different sources, integrating and analyzing the data using different tools, with the purpose to react on potential quality issues before they happen with adequate levels of data accuracy and precision. This paper discusses the role of humans in the data driven ZDM loop, considering the context of four manufacturing companies, from the EU H2020 project DAT4Zero which has also funded this study. These companies represent distinct manufacturing environments, each with specific industrial challenges and requirements, which were studied to map, analyze, and exemplify the potential role of humans in the data driven ZDM framework in real manufacturing environments.

Keywords: Zero defect manufacturing, Human in the loop, Quality control.

1 Introduction

Zero Defect Manufacturing (ZDM) is among the application areas with high potential to benefit from digitalization through the application of enabling technologies, smart products, and smart processes in manufacturing [1]. Among others, in-line data gathering, data monitoring, and advanced data analytics tools and methodologies offer many new opportunities to ZDM [2]. However, digitalization doesn't equate with the elimination of the human element from the manufacturing shopfloor. On contrary, the skilled workforce (e.g., operators, engineers) remains a critical resource for activities requiring flexibility, customization, and uniqueness, namely identifying the root causes of problems, solving them, and driving continuous improvement efforts [3]. With the recent Industry 5.0 report of EU commission [4], human-centric manufacturing is now even more emphasized. Human-centricity implies that the skilled and flexible workforce will play a key role in decision making [3], collaborating with the systems.

The literature has reached some maturity with regards to digitally enhancing the human abilities, skills, and roles in manufacturing by utilization of enabling technologies over the past decade Nevertheless, the role of humans in ZDM hasn't received much

Author accepted manuscript version of the paper by Emrah Arica, Manuel Oliveira, Torbjørn Pedersen, Felix Mannhardt & Odd Myklebust. In Flexible Automation and Intelligent Manufacturing: Establishing Bridges for More Sustainable Manufacturing Systems. 2023, 789-796.
https://doi.org/10.1007/978-3-031-38165-2_91

attention, and is considerably under-researched, requiring further exploration [5–7]. While the human aspect is largely neglected, manufacturing quality is in fact largely impacted by the human-in-the-loop [6], especially with their knowledge, flexibility, and resilience capabilities to handle the unexpected events (e.g., delays, disturbances). This paper aims to contribute to narrowing the current gap on investigating and understanding the human role in ZDM and discusses the role of humans in emerging data-driven ZDM paradigms. The study was conducted as part of an ongoing EU H2020 project, designated DAT4Zero, that focuses on developing a digitally enhanced quality management system. Case studies are presented to illustrate the human role in the digitally enhanced ZDM loop.

2 Methodology

As the researchers have been involved in the DAT4Zero project use cases actively, this study applies action research methodology, analysing and evaluating the change, and reporting the outcomes [8]. Several distinct use case companies have been part of the project with the common aim to develop a digitally enhanced quality management system, but with various types of contexts, requirements, interest, and hence involvement of humans in the processes. During the project, the researchers have conducted site visits and online meetings, planned, and coordinated the activities, identified the requirements, as well as contributed defining and testing the solutions. Collected data was transcribed, analysed, and visualized through appropriate diagrams and flowcharts, and further validated by the use case partners.

3 Data-driven Zero Defect Manufacturing

ZDM paradigm aims to avoid or eliminate defects through a set of strategies, tools, resources, and control rules [6]. Psarommatis et al. [5] categorizes four ZDM strategies; detection, repair, prevention, and prediction. While detection and repair strategies focus on eliminating the defects caused by products and process parameters, prevention and prediction strategies go beyond by focusing on avoidance of defects before they may happen. These latter strategies take a proactive approach to predict defects according to process and product conditions and avoid the occurrence and propagation of deviations in conditions (e.g., product dimensions, machine parameters) along the process chain [9]. According to [6], ZDM strategies may focus single or multi-stage processes, can be product, process, or people-centric, and may address strategic (e.g., supply chain design), tactical (e.g., quality inspection methods) and operational (e.g., product and process deviations) level effects and decisions.

Enabling technologies offer a myriad of opportunities to advance ZDM and create a digitally enhanced data-driven ZDM paradigm as summarized in the literature reviews of [6] and [5]. As a starting point of data driven ZDM, detection of product and/or process deviations as well as their correlation with defects can be further advanced with implementation of sensors, IoT, that can enable continuous collection of data from equipment, processes, and products. Such continuous data acquisition enables advanced analysis of process through big data and AI-based or simulation-based algorithms, providing more precise description of links between process/product deviations and defects. With such data-driven knowledge, process conditions can be monitored, and defects can be predicted. Consequently, data driven ZDM consists of continuous ***data acquisition*** from processes and products through sensors and IoT, ***management of acquired data*** from various sources through advanced ICT solutions, ***data analysis and modelling*** to describe and predict causal or logical links between deviations and defects through advanced algorithms and tools (e.g. simulation), and finally ***decision making*** as a feedback control on deviations to avoid defects.

4 Human in the data-driven ZDM loop

The advance of ZDM cannot be fully achieved solely by integration of digital technologies to create data-driven control loops. The human component should be considered too in order to obtain new insights and improvements in manufacturing quality [5], as well as to overcome the shortcomings of the human abilities in defect detection, especially in human-driven quality inspection [10]. In Industry 4.0, as with the previous industrial revolutions, the focus has been on the emerging technologies. However, with Industry 5.0, the focus is on the role the human operator has in manufacturing and consequently it is important to consider how humans may contribute to the advancement of data-driven ZDM. This can be done mainly in two ways: (i) by providing contributions to one or several stages of data acquisition, management, analysis, and modeling. and (ii) by taking decision making roles as empowered humans.

4.1 Human as a contributor to data acquisition and analysis for ZDM

Humans can help capturing and yielding more data from the shop floor in addition to what is accessible by means of information systems that support processes, machines, and robots. This can be achieved by their knowledge [11], or by the help of data capture technologies. For example, the operators can provide the knowledge and complex information about failures, which are difficult to detect with sensors [12]. Direct sensing of data can be achieved by sensorized AR wearable devices that can acquire information automatically as discussed in [13]. The role and contribution of humans in data analysis and modeling largely rely on their experience and knowledge to provide critical insights that otherwise could not be captured by digital tools. For example, engineers and managers may provide contributions to analysis and modeling of ZDM strategies [7]. With the help of explainable AI algorithms and reinforcement learning, humans can also contribute to re-designing the collaboration processes between humans and algorithms to improve the quality. For example, operators can teach the robot new paths to carry out quality inspection through ML [14].

4.2 Empowered humans in decision making for ZDM

The decision-making autonomy of humans can be empowered by digital technologies, along with their abilities to make effective and flexible decisions [15]. Humans with their respective roles influence or make ZDM-related decisions at strategic, tactical, and operational levels. When it comes to strategic level decisions, managers play a significant role in defining the ZDM vision and achieving what the customers want [7]. At the tactical level, humans can decide the quality aspects of an automated control system. At this level, the engineers take part to avoid systematic errors and identifying the root causes of defects, as well as investigates how to incorporate digital tools to improve the efficiency of quality control [7]. At the operational level, digital technologies can especially support and empower the operators in quality control and verification tasks. Augmented Reality (AR) in combination with process mining and machine learning technologies provides significant opportunities to assist operators in quality verification. Besides sensing, capturing data from processes, and analyzing the data retrospectively, it can assist operators in work performance by digital instructions, as well as provide automated quality verification functionalities, as shown in [13].

5 Case examples from DAT4Zero project

To better illustrate concrete cases of how human operators can be embedded into ZDM production cycles, we present case examples from the DAT4.Zero (D4Z) project. The D4Z project is a Horizon2020 project (https://dat4zero.eu/) aims to develop a digitally enhanced quality management system. D4Z builds on data acquisition, management, analysis, and modeling/utilization layers. The data acquisition and management layers generate, gather, and organize the data from shop floor resources, processes, and products, through distributed multi-sensor networks, and data integration technologies. The data analysis and modeling layers processes, simulates, and utilizes the data to support developing strategies, making effective decisions, and feedforward control mechanisms to contribute towards the achievement of ZDM in smart factories and their ecosystems. Several distinct industrial pilot companies are involved to develop and demonstrate this data-driven quality management system as discussed in below sections, along with aspects of human in the data-driven ZDM loop.

5.1 Case Example 1 – ENKI

Brief case description. ENKI is a producer of one-of-a-kind customized micro-intravascular catheters, high value single-use products that find applications in oncology, angiology, angiography, angioplasty. The products have extremely tight tolerances on the diameters of the microtubes and hence strict quality control requirements in the processes to avoid defects and waste. The critical processes to monitor and control include the extrusion of the tubes, and assembly.

The D4Z system and loop. The data driven ZDM system should firstly acquire data about the parameters of the extrusion process (e.g., temperature of the cooling bath, inner diameters of the tubes, hoppers parameters) and assembly processes important for quality monitoring and control. This is achieved by sensors; however, the accuracy of inline measurements is a challenge and should be ensured. The data is then managed and analyzed by analytical methods to form, track, and understand the insights of the fault causes and conditions, coupled with an automated fault detection system. This will allow developing efficient mitigation and control strategies.

Humans in the data-driven ZDM loop and decision making. Operators form efficient mitigation strategies with the help of decision support tools such as fault analysis system dashboards for understanding and labelling fault situations and causes. The dashboards results are generated by transparent machine learning methods to help the operators form new knowledge during use and to allow the users to build trust in the underlying decisions made by algorithms. Tools that are transparent and accountable will play a key role in efficient adaptation of AI-based systems in environments with many empirical based decisions, where operators are responsible for production issues. The operators also detect and report defects in the fault detection system, allowing utilization of their tacit knowledge and experience. Further, the catheter is manually assembled by the operator who is capable to detect and solve autonomously most of the quality issues encountered. The operator conducts visual inspection on a sample of the catheter tubes to detect a wide variety of production defects, including black spots, crooked markings, among others. But human capabilities are limited and due to the nature of the task, errors resulting to misclassification may occur. In DAT4.Zero, operators use a Head Mounted Display (HMD) that provides overlay of digital information over what is physically perceived. The software leverages the camera inputs of the HMD to extract images that are digitally magnified to improve the visual inspection. However, the HMD have additional sensors beyond cameras, namely depth camera, accelerometer, gyroscope, magnetometer, four cameras and a 5-channel audio microphone array. The use of sensor rich device supports the acquisition of numerous additional data streams related to the workflow that assist in establishing a comprehensive work context. As such, the operator is empowered to acquire seamlessly all data in the data-driven ZDM loop for analysis and traceability of the processes, as well as to detect and categorize defects, and to generate inspection reports.

5.2 Case Example 2 - DENTSPLY

Case description. Dentsply develops and produces high-precision gears for dental applications with components only a few millimeters in size and extremely strict tolerances of a few micrometers, hence high-quality requirements. One of the main quality goals is to reduce the noise created by dental rotary tools with head shaft and chuck as the major contributor components, as this is highly valued by the costumer and user. The critical manufacturing processes include the micro-grinding and micro-milling of the metal components, as well as the assembly of parts to the final product.

The D4Z system and loop. The data-driven ZDM system aims to integrating and utilizing the data on geometrical product parameters combined with integration of new sensors with focus on process data, in order to investigate and analyze the potential correlations between product and process parameters, and hence identifying anomalies and optimizing the quality control loops for production and assembly with better predictability and visualization of correlations.

Humans in the data driven ZDM loop and decision making. The production processes highly involve human operators, especially in managing the machines, offline measurement operations, and the transportation of parts between processes. One operator usually manages 2-3 machines simultaneously and performs off-line inspection methods next to the machining processes. The product process correlations should be made available to operators, engineers, and management roles to support decision making from strategic to operational levels. In the assembly area, the product variety increases the complexity of the assembly as the operator must use and check the different information for deciding consecutive assembling steps. This requires that the operators need to know many assembling processes, which means an increased probability of errors taking place, ultimately requiring rework. The visualization of the information for decision making processes is key for a “smart operator” to improve productivity, reduce failures and increase sustainability. The main goal of the solution is to reduce the challenges derived from high complexity by digitally enhancing the operator with context driven visualisation of information for improved decision-making during assembling. Mixed reality HMD again can play a critical role here to empower the operator in decision making as well as acquiring more information from processes.

5.3 Case example 3 – BENTELER

Case description. BENTELER Automotive Raufoss AS (BAR) is a producer of aluminium structural components and chassis parts, supplied to the car manufacturers. Quality defects are usually a result of issues appear in combination of manufacturing processes including extrusion of aluminum profiles, forming, punching, cutting and machining processes to make a final component before assembly. Critical characteristics and tolerances of the products are monitored at quality gates of production stages to assure the quality of the product at the end of the long value chain.

The D4Z system and loop. The data-driven ZDM system in this case also aim for developing an inline measurement and adjustment system through utilization of data from processes and products, as a supplement to the quality gates. Data utilization include acquiring data about critical parameters (e.g., positional and dimensional accuracies), managing the data, analyzing and modeling the data to estimate the deviations and improve the process control. By improving the inline process control, critical process parameters (e.g., cooling, temperature) can be adjusted and optimized to avoid defects (e.g., profile twist, geometrical deviations). Additionally, machine learning and Big Data applications are implemented to analyze the historical data and training the algorithms for predicting the product deviations during machining as well as adjusting the processes to avoid the occurrence of defects.

Humans in the data driven ZDM loop and decision making. Humans are mainly involved in the decision-making process with their tacit knowledge and experience in this use case. While the dimensional controls of the product are made and reported by a measuring machine, technicians and operators evaluate the results of the reports and take corrective actions. Furthermore, operators have a significant role in forming the fault mitigation strategies in a data driven ZDM loop. In this context, the operator's decision-making ability is empowered by digital tools such as user-oriented dashboards that can provide deeper understanding and classification of fault conditions and fault causes, as well as propose optimal control strategy for fault mitigation. When it comes to providing input to the data acquirement and analysis in the data driven ZDM loop, the knowledge and experience of technicians and operators about process states and faults can be captured and formalized by additional labelling and comment tools.

5.4 Case example 4 - FERSA

Case description. FERSA Bearings designs, develops, manufactures, and distributes high-quality bearing solutions to customers from various sectors such as commercial vehicles, automotive, and agricultural vehicles. The overall quality requirements of the bearings include high precision tight geometrical tolerances, excellent surface quality, and minimum friction. The main production processes include machining of the inner and outer rings, washing, assembling of rings with rollers and cages, and quality controls, including dimensions (e.g., height, outer and inner dimensions).

The D4Z system and loop. The data-driven ZDM system in this use case aim to avoid the following main defects: wavering raceways and burning due to vibrations and extreme temperature, leading to cracks; waviness harmonic and twist due to dimensional deviations, leading to lost oil and scrap of the part; and dimensional mismatch between inner and outer ring, leading to issues at the assembly stage. The data-driven ZDM strategies incorporate in line data acquisition from machines and processes to identify detailed process parameters such as dimensions of the products (e.g., raceway dimension) and machine controls (e.g., driver speed, driver temperature) through sensors (e.g., accelerators, temperature sensors, watt meter). Managed by the data management solutions (e.g., edge platform, datalake), the data is analyzed to identify and model the correlations between the process parameters and defects. For example, vibration analysis provides a feedback mechanism to identify the failure situation.

Humans in the data driven ZDM loop and decision making. The operators makes the process adjustment decisions, which can be empowered by the analysis tools described above. The results of the analysis guide deeper understanding of process status, which can be provided as feedback to make predictive ZDM strategies/policies via visual decision support tools (e.g., dashboard). The operators are hence notified about the anomalies before leading to defects such as burns and out-of-tolerance twists.

6 Conclusion

Case studies indicate that combining the best of capabilities of humans and technology is not only a better way to advance ZDM, but also perhaps necessary. A two-way engagement where human and digital tools complement each other's abilities towards common ZDM goals. With their flexibility and tacit knowledge humans can provide considerable contributions to the data-driven ZDM loop, especially when empowered by technology which should complement the human requirements and expectations, rather than the other way around. Naturally, workstations with manual processes such as seen in assembly operations, require more human intervention and empowerment. Future research studies should generate more knowledge on the human role in ZDM and investigate this topic more extensively.

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