Supporting Zero Defect Manufacturing Through Cloud Computing and Data Analytics: the Case Study of Electrospindle 4.0

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Abstract. Industry 4.0 represents the last evolution of manufacturing. With respect to Industry 3.0, which introduced the digital interconnection of machinery with monitoring and control systems, the fourth industrial revolution extends this concept to sensors, products and any kind of object or actor (thing) involved in the process. The tremendous amount of data produced is intended to be analyzed by applying methods from artificial intelligence, machine learning and data mining. One of the objective of such an analysis is Zero Defect Manufacturing, i.e., a manufacturing process where data acquired during the entire life cycle of products is used to continuously improve the product design in order to provide customers with unprecedented quality guarantees. In this paper, we discuss the design choices behind a Zero Defect Manufacturing system architecture in the specific use case of spindle manufacturing.

Keywords: Zero defect manufacturing · Industry 4.0. · Artificial intelligence · Cloud computing

1 Introduction

In recent years, manufacturing processes have undergone several changes to meet the ever increasing demand of customers for highly personalised and high quality products. Actually, conventional production strategies and methodologies, which have been successfully applied in the past, are impractical in the modern industrial setting [1], thus requiring more ones. Recent technological advances, such as Internet-of-Things (IoT), Cyber Physical Systems (CPSs) and Artificial Intelligence (AI), combined with the growing interest in Industry 4.0, fostered the development of a novel paradigm shift in the production process called Zero Defect Manufacturing (ZDM). This strategy aims at reducing the number of defected products to zero by simultaneously considering production planning, quality management, and maintenance management factors in a *first-time-right* fashion [2]. More specifically, this strategy leverages the huge amount of heterogeneous data generated by a company (e.g., shop floor data, product operational

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data, supplier data) to build a self-correcting system to predict and detect product defects before they propagate to downstream stages, and to continuously enhance the product design to improve its quality.

The ZDM methodology was initially defined in the early 1960 s s in the US [3] and was further developed in the following years [4]. Recent advances in the manufacturing field, combined with the data-rich environment of modern companies have fostered a renewed interest in ZDM with a vast literature of surveys, frameworks and methodologies to enable and support ZDM strategies. Psarommatis et al. [1] and Powell et al. [2] provide a literature review and investigate recent trends and perspectives in the ZDM field. Wang et al. [5] propose a general framework for ZDM in which data mining techniques play a key role. Angione et al. [6] describe a ZDM reference architecture for multi-stage manufacturing systems (e.g., automotive and semiconductor manufacturing companies) and finally Magnanini et al. [7] present a layered reference architecture to enable ZDM strategies which also relies on data generated from existing management software such as Enterprise Resource Planning (ERP) and Manufacturing Execution System (MES).

In this paper, we present a specific example of ZDM support strategy in the case of a spindle manufacturing company. Spindles are high-precision electromechanical components mounted on top of machine tools and provide rotation to the tool in order to generate working motion. They feature an external or internal electric motor and in the latter case the term *electrospindle* is used to denote such kind of devices. Spindles are manufactured in a variety of configurations and are deployed in several industrial processes, including milling, drilling or grinding for a wide range of materials, including metal, marble and wood. The *Electrospindle 4.0* project aims at applying ZDM principles in the production of spindles. Main goal is to realize new Zero Defect spindles produced by a Zero Defect production process. An innovative family of spindles is equipped with several sensors and computing capabilities; and a new production line is designed to make it more intelligent. Spindles are a representative examples of manufacturing processes of interest in Industry 4.0. Recent research focused on monitoring spindles and their health status to predict and prevent future failures. Relevant works in this field include [8] which propose a cloud-based architecture for predictive maintenance of spindles using Machine Learning (ML) techniques, and [9] which reviews research on intelligent spindles.

The rest of the paper is organised as it follows. Section 2 describes the proposed approach along with the Electrospindle 4.0 case study and finally Sect. 3 draws conclusions and outlines future works.

2 Proposed Spindle ZDM Approach

In this section, we describe in more details the proposed approach to support ZDM in the case of spindle manufacturing. A high-level overview of the methodology is shown in Fig. 1. It consists of three main steps, namely *Data collection*, *Data analytics* and *Optimization*, intended to continuously detect and predict failures and incrementally improve the product design and the assembly line. The proposed approach is currently being adopted in the *Electrospindle 4.0* project.

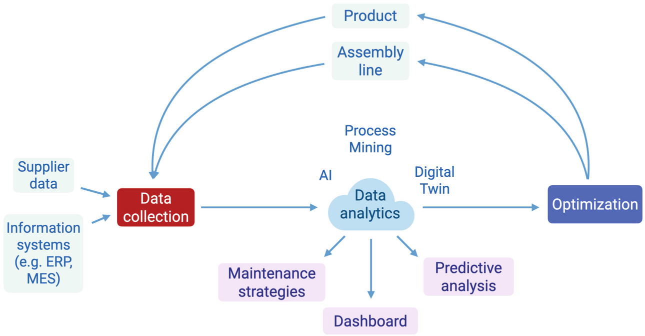

Fig. 1. An overview of the proposed approach to support ZDM

2.1 Data Collection

In this phase, data generated at different levels of the product lifecycle are collected and sent to a cloud server for subsequent analyses. Four main sources of information can be identified in Fig. 1: *(i)* assembly line data, *(ii)* data generated from the product in the customer environment, *(iii)* data stored in existing management software, such as ERP and MES, and finally *(iv)* data provided by suppliers of raw materials required to build the product. We note that the first two sources of data require the use of highly-digitalized and intelligent products and equipment to sense, collect and send data to a central cloud platform. On the other side, information systems like ERP, MES and Product Lifecycle Management (PLM) provide additional information on the production process and the product design (e.g., production planning and inventory management).

The innovative spindles designed in the *Electrospindle 4.0* project, are capable of automatically collecting several operational parameters coming from the customer environment (e.g., rotation speed, temperature, vibration, power consumption, etc.) and send them to a cloud platform for further processing. Such data will help the spindle manufacturing company to get insights on the product usage patterns from the customer. In addition to that, the production line is composed by new testing machines able to autonomously send the results of performed tests to a central cloud platform to complement data generated from the intelligent spindles and the other data sources mentioned before.

2.2 Data Analytics

Data collected from the previous step flows into a data lake provided by a cloud platform for further processing. Data comes from the several sources (as described in Sect. 2.1), however a unique central origin is needed to make analyses. Specifically, three main types of analyses are carried out in this step: *descriptive*, *predictive* and *prescriptive*. Descriptive analytics uses data mining techniques to get insights from historical data by means of dashboards or other user-friendly interfaces. Predictive analytics uses statistical or AI-based models trained on past data to predict future outcomes. Finally, prescriptive analytics leverages predictive models, together with optimization and simulation techniques to suggest corrective actions. Key enabling technologies for such analyses include AI, process mining and Digital Twins (DTs).

In the Electrospindle 4.0 project, a line of research is devoted to the estimation of the Remaining Useful Life (RUL) of spindles. Such information will be beneficial for the spindle manufacturing company to assess the health status of its products and suggest future maintenance activities (i.e., predictive maintenance). Specifically, we devise the use of recent state-of-the-art ML techniques to train a predictive model for RUL estimation using data stored in the data lake and then deploy such a model directly into the spindle (this is a case of edge computing) which in turn will use such reasoning capabilities to generate alerts or warning both to the customers and the spindle manufacturing company. Popular techniques used in the industrial settings for RUL estimation include Auto Encoders (AEs), Deep Belief Networks (DBNs), Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [10–12].

We also devise the use of DTs to create a virtual representation of devices and operations involved in the spindle manufacturing process based on [13], as wells as process mining techniques to model the production line [14] and further improve the automation level of the company. Both of them are crucial in our approach to identify critical issues in the product and the assembly line which may compromise the quality of the spindles manufactured and shipped by the company.

2.3 Optimization

Optimization builds on the analyses carried out in the Data analytics phase to support the company in improving both the product design and the assembly line. We note that this requires domain expertise to adequately address design and quality issues which may be highlighted in this step. Indeed, the current step relies on a human-in-the-loop approach to suggest corrective actions.

More specifically, insights from real-time operation data of the product, combined with past failures and faults-related data, should help project managers and designers to identify Critical-To-Quality (CTQ) components of the product and improve their design. Such information should be provided using graphical interfaces, dashboards or any other human-interpretable technique. In addition to this, models and simulations defined in the Data analytics step should also inform company experts about potential bottlenecks, efficiency or quality issues in the assembly line and provide proper steps to address them.

In the Electrospindle 4.0 project, we envision the use of recent machine learning explanation techniques and statistical analyses to extract knowledge from AI models developed in the previous step and find CTQ components of a spindle which mainly affect the RUL of the product. Also, data generated at the shop floor level, combined with DT-based simulations, process discovery and process enhancement techniques, will be used to find bottlenecks and quality related issues in the production process. Finally, we also plan to use Design-for-X [15] based methodologies to build a knowledge base of best practises provided by domain experts as well as general guidelines which will further inform and support designer to improve the manufacturing of spindles.

2.4 System Architecture

To support all the required functionalities, a mix of edge, public cloud and private cloud computing [16] has been chosen as system architecture. Machine learning (both training and evaluation) and data mining tasks will be executed using resources from the public cloud (e.g., Azure Machine Learning). Also data from the new family of spindles will be stored in a public cloud. Part of the models will be trained in the public cloud and will be evaluated directly on the spindle using edge computing [17].

A private cloud will be used to store data from information systems of the spindle manufacturing company. These include the ERP, the Customer Relationship Management (CRM) and the MES. A challenge here is the safe and secure interaction between the spindle manufacturing company private cloud and the public cloud solutions that will be used for training purposes. In order to preserve the confidentiality of company's data, data transfer flows must be designed in order to keep the data in the public cloud only at training time.

3 Conclusions

In this paper, we outlined an approach to support ZDM strategies based on cloud computing and data analytics. The proposed approach relies on the constant execution of three main steps to incrementally improve the product design and the manufacturing process, which can be summarized as the *collect*, *analyze* and *optimize* loop. We discussed those steps alongside the case study of Electrospindle 4.0, a ZDM initiative involving a spindle manufacturing company together with several industry experts and research institutions. As a future work, we plan to revisit and refine the proposed approach, and to conduct further investigations to evaluate whether the proposed approach can be readily applied to other manufacturing domains which may be significantly different from the spindle manufacturing one.

One of the technical challenge consists in the collection of a dataset big enough to allow for machine (deep) learning training. Unfortunately, the available data could be severely unbalanced. High resolution spindle data will be likely available only in certain phases of the life cycle, namely spindle manufacturing and spindle maintenance, whereas the data coming from the customers will be at a lower resolution (i.e., one measurement every 10 s), making it difficult to detect short term phenomena. This is due to the necessity of reducing the data transmitted by customers for their installed spindles. This challenge could be addressed, in principle, by adding a fog layer to the architecture, but the consortium (spindle manufacturing company and research institutions) decided that placing an additional infrastructure at the customer side is not feasible for security and cost reasons.

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