Empowering Process Quality Through Microservices. A ZDMP Perspective

Víctor Anaya, Francisco Fraile, Raúl Poler, and Ángel Ortiz

Abstract Machine learning is omnipresent in today's software solutions. One of the areas of interest that benefits from smart data exploitation is the manufacturing of products with zero defects. But manufacturing a product is the result of entangled processes spanning different companies that exchange products usually in not exclusive contracts. The machine learning promise is sustained by information. The challenges are clear: sharing an increasing amount of information along the supply chain while keeping competitive knowledge in house, reducing the complexity of implanting AI solutions and respecting heterogeneous-distributed diverse existing software systems. This paper's purpose is to present an upcoming solution from the perspective that the authors are bringing to the H2020 Zero Defects Manufacturing Platform European project.

Keywords Machine learning · Zero defects manufacturing · Software architecture · Microservices · Process quality assurance · AI as a service

1 Introduction

1.1 Zero Defects Manufacturing and ZDMP

In the last years, many industrial production entities in Europe have started strategic work towards a digital transformation into the Fourth Industrial Revolution termed Industry 4.0. Based on this new paradigm, companies must embrace a new technological infrastructure, which should be easy to implement for their business and easy to implement with other businesses across all their machines, equipment and systems.

To remain competitive and keep its leading manufacturing position, European industry is required to produce high-quality products at a low cost, in the most efficient way [1]. Today, the manufacturing industry is undergoing a substantial

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transformation due to the proliferation of new digital and ICT solutions, which are applied along the production process chain and are helping to make production more efficient, as in the case of smart factories. One of those areas is the zero defect manufacturing [2] where Industry 4.0 technology is applied with the purpose to detect, predict and prevent quality defects on the manufacturing process.

The purpose of the current article is to present the Process Quality Services provided as part of the ZDMP—Zero Defects Manufacturing Platform—EU project [3] and more specifically to introduce a serverless microservice architecture of process quality services based on machine learning and optimisers models with the purpose to address process quality assurance initiatives.

The presented work is a component part of the Zero Defects Manufacturing Platform, and as such is one of the microservices that a Zero Defects Application developer will use when providing specific defect avoidance apps.

ZDMP as a whole will be of value for an ecosystem, where software developers and integrators will provide solutions that will benefit from manufacturing infrastructure with the purpose to provide to manufacturers zero defect solutions (Fig. 1).

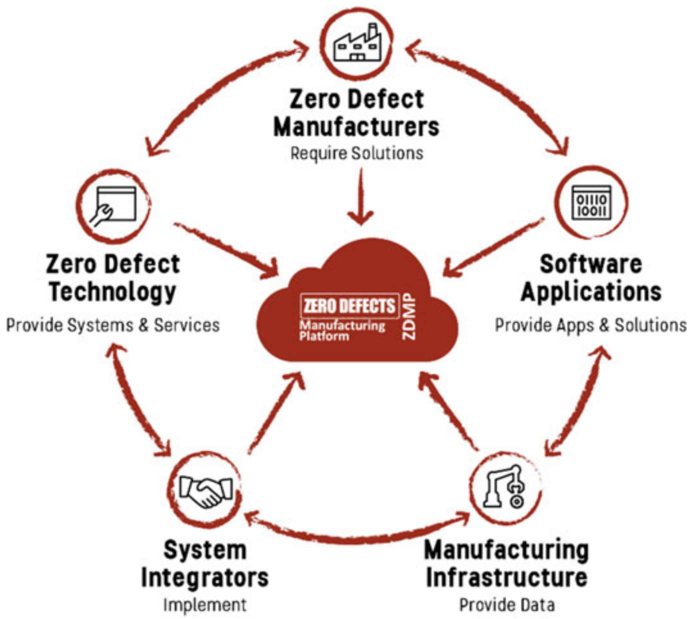

Fig. 1 ZDMP ecosystem

2 Process Quality Assurance Under the Zero Defect Manufacturing Scope

As stated in [2], ZDM implementation can be done according to a product-oriented perspective and a process-oriented perspective. The difference is that a product-oriented ZDM studies the defects on the actual parts and tries to find a solution, while, on the other hand, the process-oriented ZDM studies the defects of the manufacturing equipment and based on that can evaluate whether the manufactured products are good or not.

This paper focuses on ZDMP Process Quality proposal, focused on ensuring out-standing process quality through equipment, resource and energy efficiency by deploying novel AI-based solutions. Thus, based on the supporting services provided by the ZDMP platform, the process quality chapter will provide solutions addressing:

- **Start-up Optimisation**: Appling machine learning algorithms linked to part-flow simulation models and machine sensors to detect and correct configuration errors and anomalies to the setup and retooling of machines.
- **Material and Energy Efficiency**: Components detecting anomalies in the consumption which can also infer likely future-related defects. By identifying anomalies in use, preventative measures can be applied to the affected work centres and workpieces.
- **Equipment Optimisation**: Regression models to detect and take corrective measures to avoid machines making out-of-tolerance parts. By learning the relationship between process parameters, product properties, and quality, it allows actions on the equipment configuration to be promoted to avoid the occurrence of defects.
- **Process Quality Assurance**: Assuring the process quality and to make the manufacturing process self-adaptive. By building models of the process from other components with suitable configuration, it can adapt the optimisation goals and focus decisions on the best actions to optimise overall process quality and reduce unplanned downtime.

  ZDMP will provide domain-specific services granting the development of zApps (ZDMP applications) with quality-specific models and algorithms that will be customised for the application-specific context.

3 Process Quality Assurance Microservices

ZDMP architecture is based on the principles of flexibility and composability and as such is based around an SOA and microservices approach [4]. As stated at [5], microservices are an architectural style for developing applications from the combination of microservices a business capability, which communicate with other microservices in an application through lightweight mechanisms. With this purpose, all ZDMP components implement and publish REST interfaces allowing

Fig. 2 Process quality components

the exchange of data (primarily) with a messaging bus. ZDMP supports event-driven SOA features so that the different components can decide their interaction pattern and react to internal and external events. Following this approach, the components of ZDMP can behave either as services and/or as event producers and consumers.

ZDMP is based on a federated architecture [6], based on IIRA model [7] and RAMI 4.0 [8].

The process quality assurance component in vf-OS is composed of three services (see Fig. 2), to be known: process prediction and optimisation designer, process prediction and optimisation runtime, process assurance runtime and process digital twin.

This paper covers the process prediction and optimisation designer, a component used by zApp developers for building process quality solutions based on machine learning pre-trained models and process optimisers. The three main principles of the solution are as follows:

- Machine learning and optimisers as a service [9], where AI development complexity is lowered, through the provision of AI-based solutions targeting specific needs in vertical industries and build sophisticated models to find actionable information with remarkable efficiency.
- Serverless architecture [9] as the architectural principle supporting AIaaS (AI as a service) and OaaS (Optimisers as a Service). Serverless computing introduces large-scale parallelism, and it was specifically designed for event-driven applications that require to carry out lightweight processing in response to an event.
- Machine learning (ML) algorithm selection [10], or optimiser algorithm selection [11] according to different criteria, for instance, in the case of ML, the accuracy versus interpretability. In the optimiser case, criteria are precision and the speed of computation.

The process prediction and optimisation designer will follow a set of steps driven by the machine learning project pipeline which answer will drive the selection of a subset of microservices available to solve a given problem and its configuration

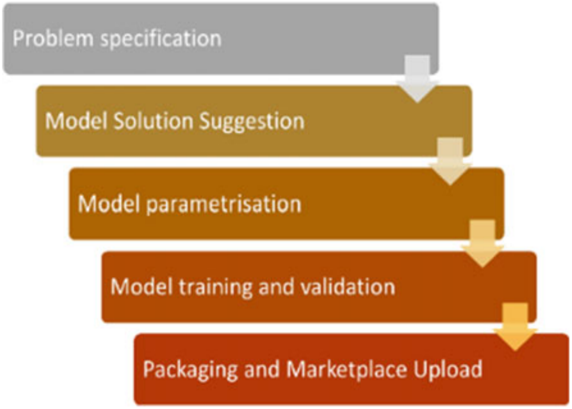

Fig. 3 Prediction and optimisation designer workflow

before deploying it to the process prediction and optimisation runtime. The stages are as follows:

- Identify the nature of the problem to be solved: manufacturing setup stage, process performance, resource consumption or other process quality assurance initiatives.
- Define a specific objective function defining the purpose at hand and expressed as the maximisation or minimisation of factors such as energy, scrap, waste of resources or lead time.
- Identify input and output data from a set of data models already pre-established.
- Specify non-functional priorities on factors such as time constraints, accuracy and interpretability.
- Select a specific algorithm, in case of being a supervised ML algorithm prepare training and testing data and train it. If non-supervised or optimisers are selected, only drive specific configuration of the algorithm.
- Evaluate performance of the algorithm and pack the model.
- Deploy the model as a serverless microservice on the process prediction and optimisation runtime (Fig. 3).

The packetised algorithm can be uploaded to the ZDMP marketplace, to be deployed on specific runtime instances of ZDMP and consumed by zApp microservices-based applications. In this final packetisation step, value-adding decisions are made. The first one, if the trained model is to be deployed along with the packetised algorithm. This model will save time when deploying the app in the production line, because minor training will be necessary, and some standardise problems can benefit from it. The second decision is the deployment model to consume the solution. In this sense, a process quality solution is a microservice offering endpoints to zApps that can be deployed to be run on a monolithic runtime or that will be run on distributed heterogeneous scenarios where services need to bring their own self-contained runtime stack. More details on this are provided in the next section of the paper.

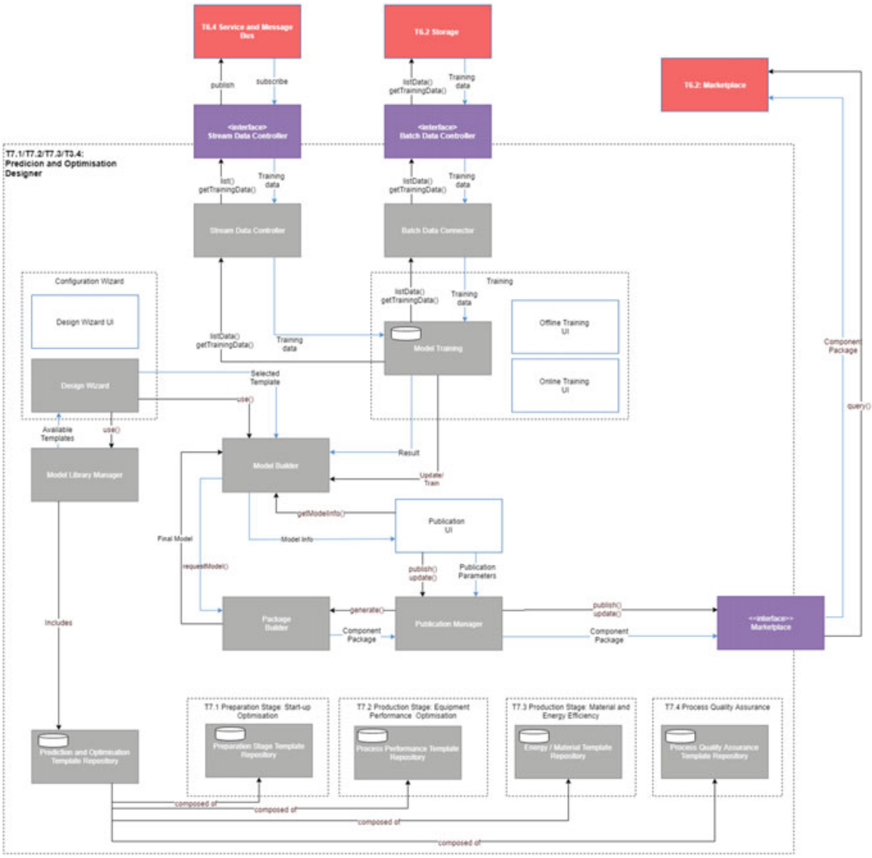

Fig. 4 Prediction and optimisation designer

The following schema (see Fig. 4) represents the internal structure and the connectivity of the process prediction and optimisation designer.

Among the main sub-components are

- **Prediction and Optimisation Template Repository**: This repository contains templates for optimisation, machine learning models and analytic techniques. Templates are linked to process optimisation or process quality prediction problems they are well suited for, subdivided in their corresponding optimisation domains:
  - Preparation Stage Template Repository: containing templates solving prediction and optimisation problems in the domain of process preparation stage (e.g. product changeover, process start-up).

  - Process Performance Template Repository: This repository contains templates related to prediction and optimisation of manufacturing equipment performance.
  - Energy/Material Template Repository: This repository contains templates to solve prediction and optimisation problems in the domain of energy and material efficiency.
  - Process Quality Assurance Repository: This repository contains templates to solve process quality assurance problems.

- **Configuration Wizard**: Allows users to select the right template for a specific prediction or optimisation problem (e.g. minimisation of resource consumption, maximisation of production efficiency, prediction of CO_2 footprint) and to configure its parameters and data sources.
- **Model Training**: Generates scripts to update and train the model according to the information provided by the user and sends the script to the AI, Analytics Designer engine via the AI, Analytics Designer interface, so that the model is updated.
- **Stream Data interface**: Interface to the publish-subscribe functions of the message bus.
- **Batch Data Controller**: This module acts as a connector to list available data sources and receive batch training data sequences.
- **Model Builder**: Builds an executable script according to the information contained in the template and the input provided by the user.

4 Process Quality Microservices. Deployment Scenarios

As mentioned in the previous section, process quality models are microservices providing endpoints consumed by zApps. An example is a machine setup configurator model based on deep learning algorithms. These microservices are queried by zApps that can contain interfaces and transaction logic that consume the microservices to provide a production-ready solution.

Deployment of microservices solutions permits sharing data between distributed components managed by different companies or benefiting of cloud solutions lowering deployment complexity and easing their adoption by manufacturers.

4.1 Cloud-Edge Microservices Scenario

The hybrid cloud is the combination of public and private cloud that in this scenario are feature rich (meaning not computationally limited) on terms of hardware, networking and storage. This is common on companies with processes done on distributed locations with specific confidentiality needs that want to share and process

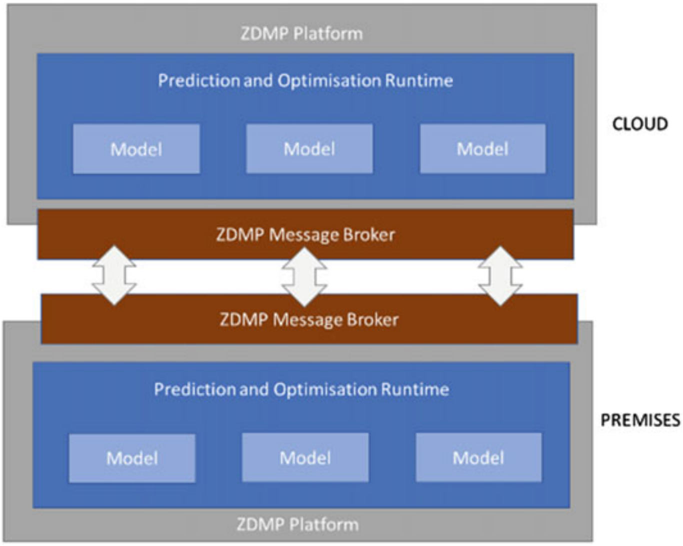

Fig. 5 Microservices on the hybrid cloud

information. In this case, two or more ZDMP Process Prediction and Optimisation Runtime Platforms run in parallel. Each of those runtimes will provide a stack of technology ranging from security, task management and training modules. Process quality model microservices will run and share the same stack of the runtime server that will be powerful but not suitable for low-power devices or appropriate for simple tasks. Figure 5 shows the schematics of this approach.

4.2 *Distributed On-Premises Microservices*

Self-contained microservices are runtime-stack-complete solutions intended for cases where limited resources are available, or easiness of a solution is necessary to limited complexity or scope of the problem to be solved at hand.

This architecture solution is common on supply chain scenarios where one company keeps a ZDMP platform and the main processes to be optimised, while other provider companies only want to share information with the first one, in the least intrusive way. An alternative business context is when low-powered devices want to preprocess data before sharing information to a functional-complete platform.

In this case, one ZDMP Process Prediction and Optimisation Runtime Platform run along with several stand-alone process quality model microservices. Each of those microservices makes minimum necessary processing before pushing information into the ZDMP platform. Figure 6 shows the schematics of this approach.

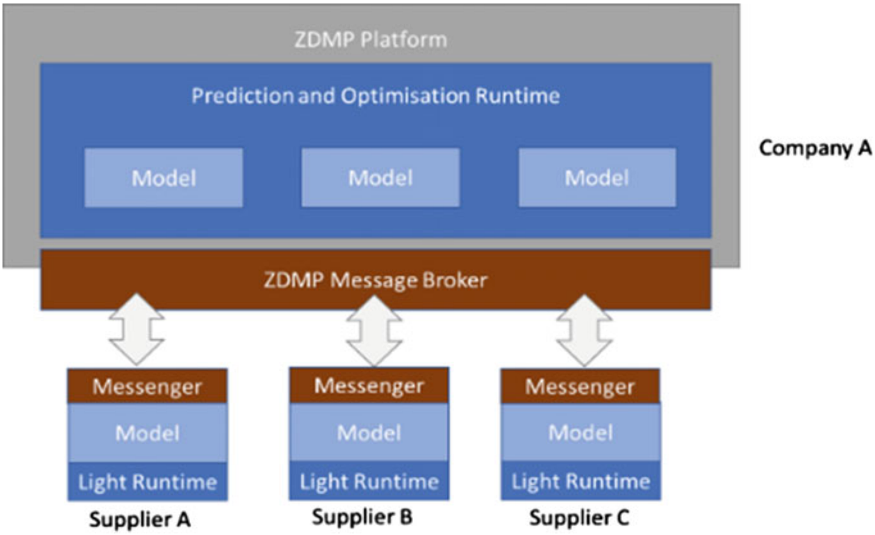

Fig. 6 Distributed on-premises microservices

5 Conclusions

This article has presented the ZDMP approach for providing AI as a service (AIaaS) and optimisers as a service (OaaS) for process quality assurance for zero defect manufacturing. The approach is fundamental as part of a broader ZDMP platform where basic core services (such as storage, data gathering or process engine) along with process and product quality assurance microservices are composed into zero defects application. The ZDMP process quality assurance is composed of four components. A prediction and optimiser designer and runtime in charge of loading, configuring, training, validation, deploying and running process quality models. The other two components are the digital twin virtualising and simulating processes and the quality assurance runtime reusing algorithms from the other two components for predicting and preventing defects.

The article has explained the prediction and optimisation designer as the core component to reusing and configuring machine learning existing models and optimisers and the key component that will pack and deploy trained models into serverless microservices. Two actual deployment scenarios have been presented. Those alternatives are not about technological concerns but about empowering the adoption of feasible solutions while respecting privacy and competences of the companies running cross-organisational quality preventive processes.

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zero defect production. ZDMP engages 30 partners (Users, Technology Providers, Consultants and Research Institutes) from 11 countries with a total budget of circa 16.2M€.

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