A Technical Approach to Achieve Zero Defects Manufacturing Process in the ZDMP Project

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Abstract

Together with product quality assurance, process quality assurance is one of the cornerstones of zero defects manufacturing in the Zero Defects Manufacturing Platform. The approach taken is to deliver partial solutions to optimise three different aspects of the manufacturing process, namely the preparation stage, the production stage, and the material consumption during production. Later, a holistic process quality assurance solution combines the partial optimization results and takes into consideration their interactions to ensure process quality.

Keywords 1

Zero Defects Manufacturing, Digital Manufacturing, Machine learning and Artificial Intelligence

1. Introduction

This chapter describes the technical approach to develop solutions to control manufacturing process quality, through the supporting services provided by the Zero Defects Manufacturing Platform ZDMP. The approach is based on preventive and corrective strategies to avoid quality losses, by extracting meaningful insights from sensor data, as well as other data sources. Preventive strategies rely on machine learning to model the relationship between the process quality and incoming data in order to predict, and consequently prevent a manufacturing defect. Corrective strategies rely on reasoning and statistical techniques to optimise the manufacturing process configuration so that defects are detected and corrected [1]. Quality Management is carried out at different quality control stages along the manufacturing process [2]. ZDMP process quality initiatives cover three of these quality control stages, being Pre-production stage, Production stage, and Production stage: Equipment Performance. Sections 1.1, 1.2, and 1.3 describe the main goals, milestones and current status of the technical developments foreseen in each category. Through ZDMP applications, the (possibly contradicting) decisions obtained from these models will be merged and balanced by novel manufacturing operations management solutions, which will interact with users (managers and operators), and Industrial Control Systems so that it becomes an interface between them with the following objectives: Predict and prevent losses, provide deeper process insights and analytics to users, and learn from the decisions made to enhance process automation. Section 1.4 describes how the ZDMP project plans to materialise this vision.

2. Pre-Production Stage: Start-up Optimization

The scope of Pre-Production Stage is to deliver solutions, heavily based in machine learning, to support self-configuration and start-up optimisation of production lines. With the help of machine

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learning algorithms, it is made possible to detect and correct organisational errors causing availability losses. This reduces equipment changeovers and eliminates related errors. Sensors can provide information about the status of the process, the equipment, and the surrounding environment as [3] and [4] demonstrated. Machine learning models are able to predict unplanned stops well advanced in time [5], so that the condition that might lead to them can be avoided, e.g. by changing the configuration of the machine or the sequence of operations [6]. Reasoning techniques are used to determine the specific change in each particular scenario. Digital models of the process that run in parallel with the real equipment are used to apply these corrections in the preparation of the process.

One of the use cases in the automotive sector serves to better illustrate this vision. The specific objective is to detect and prevent errors in the machining of engine blocks. A sensor gathers 3D information from the surface of the cylinder block and provides data about the state of the process. This information is pre-processed using image processing and statistical analysis software to obtain data about the state of the process. A data-driven prognostic model supports the optimisation of the machine. For the model building, the multi-stage modelling approach is used. The technical challenge is proper data recording/collection so that the process values are traceable for each product or batch of product among the multiple stages. For the given use case the influence of the separate stages and the combination of them in the quality of the prediction is analysed and the proper method/procedure for fusing the date from the separate stages is determined [7], [8]. Currently, the consortium is working on the integration of the sensor and the collection of data to build the first prediction models of this use case.

3. Production Stage: Material Resources

Regarding predictive approaches, the objective at this stage is to develop machine learning models able to infer possible future defects related to anomalies in the consumption of energy or material resources. Furthermore, the aim is to improve the predictive capabilities of the system, using sensor to track the consumption of any material or energy resource and machine learning models that are able to detect anomalies and predict quality loss [9]. The modelling approach at this phase is to employ rule-based models. Additionally, process parameters and energy use will be also integrated into such models to allow a fine-tuning of the system, so that a corrective approach can be implemented. The idea is to propose decisions on the best actions to optimise overall process quality. On the other hand, the intention is to obtain a much quicker and stable training process that requires fewer sample data for training. Furthermore, those models will be sustained by part-flow simulation [10] e.g. to accurately predict the throughput of a production line, what is an important aspect to take into consideration when forecasting energy and material consumption.

ZDMP will exploit several models for industrial process energy and materials efficiency control. One of the cases is ZDMP pilot on moulds manufacturing chain, where it will be developed a process alert system for machine tool failure prevention. Such system will be able to automatically gather and store equipment and machining process data to detect sudden or abrupt changes that can lead to a premature failure. Additionally, the system will calculate deviations from standard working conditions that could lead to near failure events using data analysis algorithms, that will allow for corrective actions. The companies participating in this use case are interested in reducing costs and the number of waste parts generated. Additionally, a second use case referred to as electronic products manufacturing will be developed, where the same ideas will be applied to component inspection tasks.

4. Production Stage: Equipment Performance Optimisation

At this stage, black-box regression models will be used to detect and take corrective measures to avoid machines resulting in out-of-tolerance parts [11]. The regression models will learn the relationship between process parameters, product properties and quality, and will be able to guide actions on the equipment with a view to avoiding the appearance of defects.

A pilot implementation is being developed for a moulds manufacturing chain. More specifically, machine tool failure prevention is aimed. At this stage, data and knowledge transfer is taking place between all nodes in the moulds manufacturing chain (spindle producer, machine-tool builder, and final moulds manufacturer) and the solution developer in order to set: target parameters, dataset format and storage and usage procedure. Once all this is set, most suitable algorithms will be selected and developed for online quality trend prediction, stabilizing the training process via methods based on active learning (for sample selection) and concept drift detection. Based on this prognosis, most effective correction loops (e.g., fabrication parameter tuning) will be discussed along the production chain.

Also concerning the equipment performance optimisation, an upgrade for the anti-collision system of the CNC machines involved in the aforementioned chain is being developed. This upgrade takes advantage of a 3D scanner so that no part in the machining chamber (e.g., clamps) is left unconsidered by this safety system.

5. Process Quality Assurance

In the scope of ZDMP, Quality Assurance makes use of quality control and predictive techniques covered in start-up optimisation, equipment performance optimisation and material and energy efficiency, along with other post-production techniques such as predictive maintenance with the purpose to prescribe action for defect avoidance and make the manufacturing process self-adaptive.

From this vision, Artificial Intelligence acts as the new interface for manufacturing operations management. In the backend, it builds a mathematical model of the process using the different optimisation goals and balances them to propose decisions on the best actions to optimise overall process quality. In the frontend, it streamlines processes and workflows, simplifies decision making for both managers and learns from events and decisions to curate the models. The learning approach will be based on clustering, assuming the existence of typical situations in the production line for which a characteristic set of possible actions exists.

Quality Assurance will articulate that decision-making process-scoped approach through its integration with a digital twin component that will provide a virtualised view on the process parameters and configurations along with simulation capabilities to evaluate the different alternatives according to the predicted values generate by the AI algorithms **Erreur ! Source du renvoi introuvable.**. Rich visualisation techniques for decision making will be provided.

A ZDMP construction pilot based on the supply of construction materials of two different suppliers to a construction company advised by a construction project management supervisor company will make use of the process assurance component. Data on product quality from suppliers, along with the construction project planning and predicted quality will be fused on quality assurance reports where process rescheduling could be necessary or machine reconfiguration for specific raw material flaws could be needed to make the most of products with different levels of specification conformances

6. Conclusions

This paper has introduced the Zero-Defect Manufacturing Approach considered in the ZDMP EU project from the perspective of Process Quality Assurance through equipment, resource, and energy efficiency based on machine learning solutions and optimisers models. ZDMP provides a complementary Product Quality Assurance perspective were product quality is predicted, inspected and tested. ZDM Process Quality Models will make use of industry 4.0 sensors and CPS technology to ingest data for detect, predict and prevent process motivated defects. The resulting algorithms and models provided will be available as part of the ZDMP toolkit solutions for building zApps, that is Zero Defects Applications exploiting machine learning based services for solving industrial quality related problems, through a microservices approach.

The approach will be validated based on four different pilots covering the range of tasks and initiatives within the scope of ZDMP. These pilots range the automotive sector, tooling sector, electronics sector and construction sector. Zero Defect Initiatives cover the different stages of the manufacturing from, from pre-processing, inline processing and post-processing of manufactured products. The different root causes of process defective execution has been covered, as equipment, resources and energy efficiency are considered.

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