Modelling, predicting, inspecting and supervising product quality for Zero Defects Manufacturing in ZDMP Project

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Abstract
This paper describes the technical approach to develop solutions to control manufacturing product quality based on the different supporting services provided by the Zero Defect Manufacturing Platform. Solutions are based on both preventing and inspecting functionalities, relying upon sensor data and other product and process information.

Keywords 1
product quality, machine learning, artificial intelligence, anomaly detection, non-destructive inspection, Digital Twin

1. Introduction

Preventing strategies can be split into two different approaches. One described in section 3 dealing with quality prediction techniques, relying on machine learning to model correlation between the product quality and data collected from sensors during production stages, thus anticipating important defects and achieving savings in term of cost and time. The other described in section 5 deals with supervision tasks focused on the identification of anomalies and critical trends during production, also facing unsupervised scenarios where the product quality labels are missing. Both approaches are executed in autonomous way, under minimum human intervention. Described in between, section 4, there is the component of automated non-destructive product inspection: taking advantage of various types of visual sensors and processing tools also based on Artificial Intelligence, it allows the detection of a whole range of defects, ranging from dimensional to surface finishes.

Somehow transversal to all these analytical predictive and inspecting solutions, section 2 introduces the generic requirements framework comprising the characterization and modelling of the product and its components down to the implementation of Digital Twin functionalities.

2. Characterization and Modelling

In terms of establishing a Product Quality Assurance framework, a first important step involves the characterization and modelling of all materials and components of any product, in a factory that seeks to guarantee zero-defect scenarios in its production processes: it is also crucial to define the specificities of each product and how these should be incorporated into the production processes. These functionalities will be implemented inside a ZDMP service able to handle:

- Material characterization, (i.e. to define physical, chemical, mechanical and microstructural properties of materials).

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- Physical product description (i.e. component identification and tolerances, assembly relationships, Bill of Materials, etc.).
- Virtual product modelling (i.e. Digital Twins to have a digital representation of a product).
- Methods for the traceability of the product.

The idea is to make use of the concept of Digital Twin (DT), to gather all this information into a digital representation of the product, but also of the related processes. In [1] it is said that a DT consists of three parts: physical product, virtual product and the linkage between both, that serves as a bridge between the physical and the digital world. [2] mentions that DT refers to a comprehensive physical and functional description of a component, product or system, which includes useful information about the current and subsequent lifecycle phases, extending the concept to what underlies the product itself. [3] introduces PLM (Product lifecycle management), saying that a DT allow companies to converge cyber and physical data to also serve product lifecycle, to drive product design, manufacturing, and service to be more efficient, smart, and sustainable.

Within this framework, a general-purpose version of the DT tools will be available as a first prototype, which will be tuned and adapted through subsequent iterations to the diverse pilots considered in the project. It will be first checked in a use case of a factory that produces moulds for plastic injections with a milling machine using an in-line 3D modelling and then in an another use case of an assembly line of electronic automotive instrument clusters and display products, with AI-supported optical defects detection.

3. Pre-Production Stage: Product Quality Prediction

The aim of this task is to predict the quality of the product and anticipate possible defects arising during manufacturing process: this can have a double advantage, on one hand avoiding unnecessary further manufacturing steps, on the other it can help to redefine production parameters or initial conditions (materials) as corrective actions to restore quality threshold/level. Both preventive actions are pivotal in a zero-defect perspective and will rely on a set of machine learning (ML) techniques, mainly of supervised type, in order to infer relationship between the different parameters monitored along the production chain and the quality of the product; this can be represented by discrete categories (for example: good, to-be-rejected, to-be-reworked) or continuous quantity, which discriminates between classification or regression models.

Product quality can be labelled through different procedures, ranging from Destructive Testing techniques of selected samples, automated Non-Destructive Inspection (see next section) down to visual inspection performed by plant operators: when building performing models, the reliability of quality indexes must be considered. On the other side, like in any other machine learning training step, several issues must be taken into account, such as the presence of missing data, outlier removal, feature engineering, time series analysis and many other factors that can influence model performance. Once the prediction model is trained, it is possible to simulate other process conditions, preserving the internal correlation structure of the data. Then, an optimization step could be performed in order to obtain new process conditions that maximizes (or minimizes) one or more quality variables, once constraints are imposed to avoid excessive model extrapolation which will cause model performance deterioration.

Another interesting feature of the ZDMP implementation of quality prediction models is that a continuous training mechanism will be envisaged in order to improve the model performance, learning from most recent supervised dataset, when these are available. For model comparison and improvement, standard evaluation metrics will be available during training procedures.

These predictive technologies will be tested in an automotive industry scenario that involves the production, machining and assembly of aluminium engine blocks: production, through aluminium injection, and machining are processed on separate companies and some quality defects appear only after machining. The ZMP platform will help in integrating information and correlate it in order to allow predictive and preventive actions, reducing production costs and improving production process.

4. Production: Non-Destructive Inspection

This task involves the detection of defects during the manufacturing production activity through Non-Destructive (ND) Inspection techniques which can be applied at different phases of the production: starting from pre-production raw material inspection, moving through in-line inspection at specific (and possibly smart) production stages down to the inspection of the finished piece. The set of sensors and analytical tools implementing ND analysis is aimed not only to detect defective parts for rejection or re-work but also to assess some quantitative quality indicators for the monitored products: such indicators can be used to define more sophisticated operation, like the re-assignment of the piece to specific production final delivery as a function of different requirements, or identify quality trends to anticipate quality deterioration and so react in advance. Product quality is probably one of the major drivers with respect to all other criteria and quality indexes including the ones related to process analysis: when optimizing equipment set-up or energy efficiency, the constraint that this operation must not affect product quality or just at a minor extent is always to be considered. Moving towards a generic zero-defect perspective, by monitoring the product quality it becomes possible to find correlations with other process monitored parameters, as well as material characteristics, which opens interesting and valuable opportunities for a ZD manufacturing as described in previous paragraph.

Non-Destructive testing is a wide group of analysis techniques, so to detect different types of defects such as dimensional, welding, machining, painting and surface finishes. These techniques include methods based on eddy current, vibrational analysis, imaging (radiography, artificial vision on digital images, …), optical analysis and many others. More specifically, regarding the implementation for the ZDMP services, a big focus will be on artificial vision techniques including also Artificial Intelligence technology, which brings a high degree of innovation and has also proved to be versatile for a wide range of applications. Indeed, this choice also fits to the requirements coming from ZDMP pilots and matches to the specific skills of one of the technical partners involved in the implementation of this platform component.

For example, the quality inspection functionalities will be significantly used in the context of a ZDMP construction pilot, where the possible defects on a stone slab after cutting and polishing must be automatically detected and classified in order to drive decisions about how to proceed for further slab cutting aimed to manufacture tiles for construction: this allows to save the actual extra-costs of operator manual inspection. Finally, the conformity assessment of the finished tile shape according to expected design will also make use of artificial vision inspection functionalities.

5. Production: Supervision

The objective of this step is to monitor each individual part along the entire supply chain, collecting all relevant information in the process, with the aim of identifying critical trends that might result in possible downstream defects. Here we can differentiate two scenarios: unsupervised and supervised.

In the unsupervised scenario, no product quality variable is available. This can be somewhat common in SMEs because of lack of resources to perform quality tests. Another cause could be technical difficulties to obtain product quality data. In any case, ZDMP will implement a Multivariate Statistical Process Control (MSPC) methodology based on Principal Component Analysis (PCA) to face those situations [4] [5]. This methodology is based on two stages. In stage I a PCA model is trained using process data under Normal Operating Conditions (NOC). In order to achieve this some data cleaning has to be done (possible missing data imputation, outlier removal, …). Once the model is trained the Upper Control Limits (UCL) of two statistics are computed (Squared Prediction Error -SPE- and T^2 Hotelling's statistic). In a second stage the model is used for prediction: when a new observation is received, it is projected onto the latent subspace and the two statistics are computed. Then, if some (or both) of them are over its corresponding UCL then we can suspect that the process is outside NOC conditions and the product is susceptible of presenting some defects. Another important aspect of this methodology is that, once an abnormal situation is detected, contribution plots derived from the corresponding statistics can be used in order to know which variables are responsible of such anomaly. This contributes to a better process understanding.

In the supervised scenario there are one or more variables that measure product quality. In those cases, it is possible to relate process conditions to those quality measures using Machine Learning algorithms. Specifically, ZDMP will use Partial Least Squares (PLS) to perform this functionality. PLS is a multivariate regression technique able to predict not only the response variable (i.e. quality variables) but also the predictors variables (i.e. process variables). PLS is also able to predict more than one response variable at a time. Thus, applying the same MSPC methodology as above, ZDMP will be able to detect abnormal situations both in predictor variables and response variables and to identify which process variables are responsible of such abnormal situations.

Those technologies will be tested in an automotive industry scenario that involves the production, machining and assembly of aluminium engine blocks. This will involve two factories. The first one is responsible of engine block production, which is divided into several stages: injection moulding, refrigeration, heat treatment and impregnation. A supervision model will be implemented in each production stage to detect abnormal conditions that could lead to engine defects. The second factory is responsible of the machining and assembly. In the same way, a supervision model will be implemented to monitor these processes and detect abnormal situations.

6. Conclusions

This document has introduced the analytical tools and services in the perspective of the Product Quality Assurance for Zero-Defect Manufacturing Approach as conceived in the ZDMP EU project. Inspecting and predicting techniques for control of product quality are based on machine learning models analysing data collected from production in-field sensors and other production related information. These tools will be available on ZDMP to allow the design and construction of zero-defect applications and solutions to maximize the product quality, also relying upon other useful services provided inside the platform. Between them, Process Quality Assurance services can be considered somehow complementary to Product Quality ones, but rather focused on prediction and optimization of overall process-related targets, like material and energy optimization and equipment organization.

ZDMP pilots cover four different industrial scenarios, namely automotive, machining tools, electronic and construction sectors; each of these will make use of the here described functionalities for Product Quality Assurance, and in particular all main purposes of prediction, inspection, supervision as well as the concept of Digital Twin will be tested.

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