IoT, Risk and Resilience based Framework for Quality Control: Application for Production in Plastic Machining

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Abstract: The definition of defect prediction models in manufacturing emerges as an attractive alternative supported by industry 4.0 concepts and solutions. We propose in this paper an IoT-based approach for a global quality control mechanism in industry. We cover in this work the in-process quality control inspection, the production machines as well as the production environment monitoring. Our framework addresses data analytics algorithms using monitoring data, risk assessment models, resilience parameters and acceptance criteria for prediction models. The proposed concepts are implemented to control the manufacturing processes of a plastic product where the distinction between irregularity and nonconformity needs to be supported by a smart decision system.

1 INTRODUCTION

The fourth industrial revolution brings the concepts of digital transformation and connectivity between cyber and physical assets (Zamiri et al., 2019). The massive digitalisation of business activities in industry is supported by facilitating the adoption of new technical enablers, open APIs, etc (Lade et al., 2017a). To formalise activities in collaborative networks. The connectivity is addressed by the integration of IoT networks, cyber-physical systems, cyber-physical production systems, etc. as solution to increase the reactivity of the industrial assets to build more smart systems (Lade et al., 2017b). For product quality control in manufacturing, the new technological solutions and paradigms are challenged to support more preventive approach for in-process quality control. We aim to increase the sensing capabilities during the manufacturing steps (in-process) to collect data about machines, products and environment. The collected data need to be contextualised by adding risk and resilience criteria and then trained to propose predictive model for product conformity assessment.

We analyse in the second section existing research contributions dealing with product quality control solutions and covering the concepts of IoT-based data analytics, risk management and resilience. We detail in the third section a functional view about the proposed Framework with the main building blocks necessary to design and develop a global quality control system. The fourth section provides some technical details about the implementation of the proposed concepts and their application on the quality control of a plastic product.

2 RELATED WORKS

To set up a resilient quality control system, we analyse in this section: the connection between resilience and quality control, the applicability of machine learning techniques to define quality predictive models and the definition of resilience requirements to improve the efficiency of the quality control mechanism.

2.1 Resilience in Quality Control

The evolution of technology during the last decades have forced us to remodel solutions used for product quality control in industries and to improve resilience systems, especially changes related to human-computer interface along with the continu-

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ous evolution of information technology from cloud computing, big data, internet of thing (Tsang et al., 2018), machine-to-machine communication (Pereira et al., 2019), Cyber Physical System (Lee, 2015), Social-CPS derived from fundamental artificial intelligence algorithms about machine learning (Shahbazi and Byun, 2021), data mining, knowledge engineering, sensor network, Software Defined Network (Ali et al., 2017) and so forth. In this section, we refer to some works that have opted to use these technologies to propose improvements in control and resilience systems for product quality. (Herrero et al., 2002) propose an integrated quality and safety management system based on a systematic approach for quality and safety management. Enforcing the barriers for improving quality, safety and reliability concept of technical systems, equipment, and various components which are the main ideas and which are also represented and confirmed in (Celik, 2009). As well as, (Kaar et al., 2018) have proposed a Resilient Ontology based on different standards, concepts, and frameworks. This ontology ensures a higher quality data integrity. Furthermore, it provides the environment with an improved resilience in order to obtain a new higher quality data. (Reis and Gins, 2017) propose three major stages of industrial process monitoring in the context Big Data - Industry 4.0 (detection, diagnosis and prognosis) for root cause analysis and important diagnosis obtained for quality improvement. In addition, (Al-Shammari et al., 2020) have proposed a new resilience technique for internet of think networks dealing with, among other things, resilient service embedding with sensor actuator node redundancy. The aim is to reduce potential attacks and data loss by enhancing reliability and accountability, with real-time data collection. (Wang et al., 2018) targets building an in-depth model to effectively detect defects in products. This model is based on deep convolutional neural networks. The results show that the model is able to categorize the image sample in the correct image class and indicate whether it contains defective regions or not. Equally, the resilience maturity model presented in (Marrella et al., 2019), is based on a design-time, date-centric maturity. It is an extension of the case management model and notation. This model is a real tool to provide support for process designers so that they may become aware of how resilient their processes are. In fact, authors have confirmed that a proper analysis of involved data allows the process designer to identify possible failures.

2.2 AI and Machine Learning for Quality Control Decision Support

The use of AI and machine learning techniques for quality control decision support is commonly addressed in the literature. (Dey et al., 2020) introduce the key idea is to join a simulation approach with machine learning models. This allows to determine the optimized parameter values of checkpoint intervals and checkpoint counts for different configurations to improve quality control. In (Tellaeche and Arana, 2013), a process for quality control for plastic injections was developed using machine learning algorithms. (Benacchio et al., 2021) use the same learning approach to present some recommendations for resilience strategy based on performance, efficiency and effectiveness. These recommendations have an impact on hardware developments. (Escobar and Morales-Menendez, 2018) and (Escobar and Morales-Menendez, 2017) have proposed a learning process and pattern recognition strategy for quality control based on machine learning techniques. They have formulated the defect detection as a binary classification problem. They have also proposed an approach to detect rare quality events in manufacturing systems and have identified the most relevant features for product quality. The experimental results confirm that 100% of defects can be detected effectively. For the monitoring of industrial machines and structural health (Bhuiyan et al., 2017) and (Mohanty et al., 2015), the authors have proposed a solution for a low-complexity signal processing where the sensor reduces a significant amount of data without sacrificing the quality of data. As well, they present a decision-making algorithm by which each sensor can make a decision on its acquired data, so communication is reduced without using inconsequential data. (Farahani et al., 2019) use a sensor network to collect data about operations of injection and molding. This data was then synchronized and integrated with the machine data to have the maximum variety of online time-based data sources. Thereafter, all data was used in predicting variations on quality indices of the final product, namely weight, thickness, and diameter. In the same way, (Berger et al., 2017) presents the optimized operation of both 3D and 2D measurement systems in line production, which are used to detect defects that appear in the production of hybrid metal components in the resin transfer moulding process.

2.3 Resilience Requirements

In the literature, a resiliency is defined by ”the ability of a system (here a manufacturing system) to recover from an undesired state to its desired state" (Hollnagel et al., 2006), (Sheffi, 2007). The attributes of resiliency of a production system are defined by persistence, adaptability, agility, redundancy, learning capability, and decentralization (Schmitt et al., 2017). Within the development of new technologies used in information systems, resilience engineering began with the study of safety systems. Also, resiliency is one of the six characteristics of smart manufacturing which are data-driven, networked, connected, resource sharing, resilient, and sustainable (Kusiak, 2019). We believe that the resilience of a system is measured by its ability to be adapted to new organizational requirements and unforeseen changes that were not initially defined in the first design of the existing system. This means that a resilience system is able to automatically adapt to such changes (Müller et al., 2013) and (Rosemann and Recker, 2006). In order to apply this affirmation and improve the resilience of our system, the first essential step was to define a Requirement Resilience set. In many literatures, several studies have focused on defining the resilience requirements, as illustrated in this paper (Marrella et al., 2019), authors have proposed a method that helps the process designers improve their process models by considering their previous failures generated by unavailability data. The authors have given a prerequisite that needs to be satisfied in order to model a resilient process for business. In addition, in these papers (Agarwal et al., 2014) and (Agarwal et al., 2014), authors have identified the requirements for the resilient nuclear power plant outage control. These requirements concern information of nuclear plant operation, process automation and process of data collection/processing techniques for the improvement of a resilient nuclear power plant outage control.

3 RESILIENT QUALITY CONTROL FRAMEWORK IN MANUFACTURING

In the context of industrial manufacturing, the setup of a global approach for in-process quality control requires the definition of three control levels: the manufacturing resources (machines, humans, etc.), the product during the transformation processes and finally the work-cell environment where external conditions can impact the quality of the product. In addition, control results are collected from the traditional quality control process after the manufacturing phase. The following figure (Figure 1) presents an overview about the proposed Framework.

3.1 Sensors Network Design

The design of the sensor network must ensure the observability of the variables, the detectability and isolability of faults. In this step, it is necessary to analyse the sensor location based on several indicators such as redundancy, observability, precision, estimation and reliability of the measurement system. In our case, the sensor's network design process is defined using the manufacturing machine-sensing capabilities, the product dimensions and tolerances, the characteristics of the manufacturing environment and finally the history of the nonconformity problems and their origin. To ensure data reliability, each selected sensor must be replicated (similar sensitivity, but different brands), to ensure the reliability of collected data. The first round of harvested sensors is defined so as to provide a direct set of usable data to treat the most common origins of quality problems and nonconformity.

3.2 Sensing Network Monitoring

A good sensor network monitoring must meet three requirements. First, it must be responsive in order to analyse the data quickly and correctly. Second, it must evaluate the correct operation and the status of the network. Third, it must make the data from the sensor network available to the user and present this information in the requested format to be processed efficiently.

3.3 Risk Identification and Assessment

The systematic use of all available information to identify and to estimate the risk is required for risk analysis . It is necessary to apply a procedure, based on risk analysis to minimize product failures. This approach is completed for a risk assessment step in order to ensure a global approach. Among the different nonconformity problems, a first classification is provided (cost, delay, Return on Investment, environmental, etc.) which have the most impact on quality problems and, if available, their origins. We propose to define the risk quotation according to the impact of the observed nonconformity. Therefore, risks definition depends on the product to control as well as the production conditions and the work-cell environment.

3.4 Machine Learning for Decision Support

This step is based on the previous results. The data from the sensor network is used in the experimentation of different ML algorithms in order to make

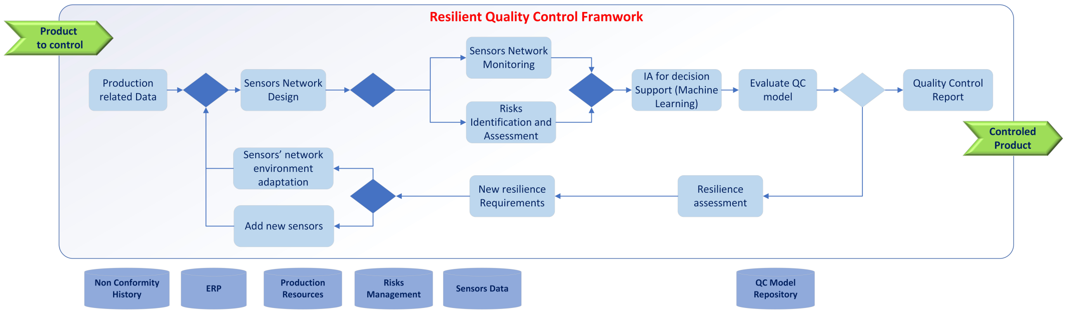

Figure 1: Resilient Quality Control Framework in manufacturing.

their analysis and make the right decision according to the defined requirements. To build our quality control model, we consider the following inputs: the sensor's monitoring data (collected from machines and control tools during the transformation operations), the risk quotations related to the nonconformity problems (qualitative data to be normalised), and the quality control results evaluated after the manufacturing stage. Using machine learning technic, we design a prediction model for product defects predictions.

3.5 Evaluate Quality Control Model

To evaluate the proposed quality control model, we consider the following criteria: the redundancy of detected errors, the sensitivity of the model, and the trade-off between prediction model precision and recall.

3.6 Resilience Assessment

For the resilience assessment, we adopt an indicators-based approach. A resilience indicator is a description of information that is used to identify the state of product quality. This information is qualitative and measurable in accordance with the defined requirements. A set of indicators can measure the resilience characteristic. The resilience indicators can be the outcome indicators or process indicators. In our case study, we select the most adapted set of indicators (common availability of raw data) from the one introduced in (Jain et al., 2018):

- Phase I – Avoidance: Alarm rate, Unplanned maintenance jobs, Unplanned shutdowns per year;
- Phase II– Survival: Mechanical device shutdown, Safety critical equipment (SCE) inspection, Safety critical equipment (SCE) deficiency;
- Phase III – Recovery: Tests for emergency systems and procedures, Mock drills for emergency situations;
- Common metrics: Process safety required training sessions completed, Required procedures reviewed/revised.

3.7 New Resilience Requirements

After the resilience assessment, in this step we investigate the possibility of adding resilience requirements to improve the quality control model of the product. In fact, its requirements must comply with the conditions of the step ”Sensing network monitoring” setup. Therefore, our resilience requirements are related to the:

- The number of sensors data considered in the prediction model;
- The criticality of the risks considered in the prediction model;
- The trade-off between precision and recall in the prediction model.

3.8 Sensor's Network Environment Adaptation and Add New Sensors

According to the previous evaluation results of the quality control model, we propose a feedback mechanism to ensure the minimal distribution of the sensors network to maximize the robustness of the quality control model. A system is considered resilient if its capabilities can be adapted to new organizational requirements and changes that have not been explicitly incorporated into the design of the existing system. To ensure this capability, our resilience requirements tend to maximize the number of sensors participating in the definition of the quality assessment model. For sensors environment adaptation, we proceeded with changing the sensors' location or their calibration. For sensors augmentation, we proceeded by replacing sensors with low sensitivity. For conflictual situations, we added new sensors in different locations to better adapt our quality gates.

Table 1: Overview of monitoring data.

Scope in production	Monitoring Perimeter	Monitoring data from sensors	Evaluated risks
Manufacturing	Operation resource: Machine	Temperature, depressions, throughput, time, position, material fluidity, etc	Breaking of manufacturing tools due to aging Breaking of manufacturing tools due calibration problem Wrong machining parameters or tools
Manufacturing	In-Process Quality Control	Quotations, product centricity, material thickness, 2D coordinates of the spots, 3D coordinates of the spots	Adaptability of machining speed with ongoing product Wrong machining sequence Level of light needed for laser measurement
Manufacturing	Work-cell environment	Temperature pressure humidity	Cleanliness of the manufacturing environment (presence of material fragments)
Quality Control	Quality Control for finished products through 3D image processing	Quotations, product centricity, material thickness, 2D coordinates of the spots, 3D coordinates of the spots	Position of the sensors Level of light needed for laser measurement Level of precision-time for control

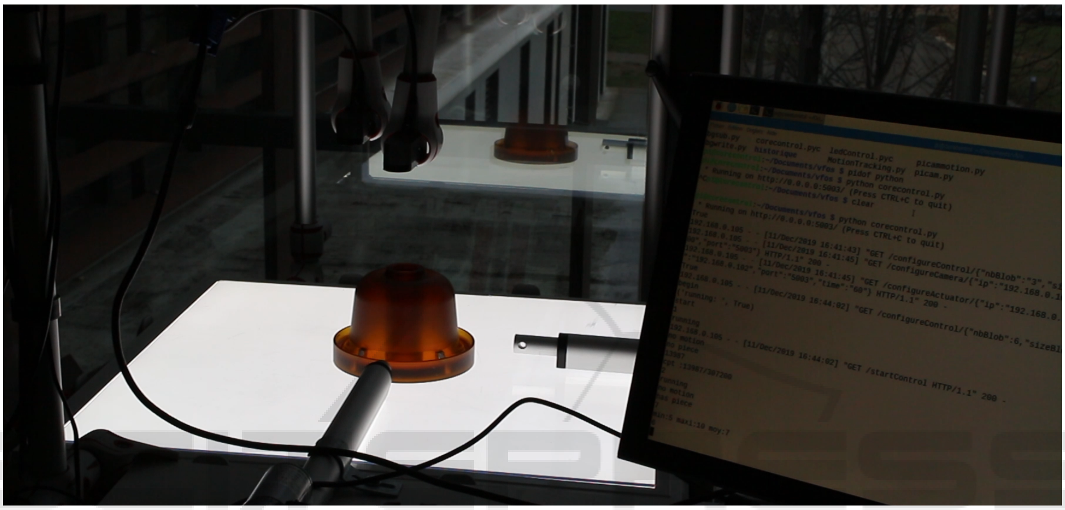

Figure 2: Quality control after manufacturing.

4 IMPLEMENTATION AND CASE STUDY

We implement the proposed concepts as detailed in the previous sub-sections for the in-process quality control of product machining in the plastic industrial. Our main goal was to detect the sources of non-quality at the earlier stages of the machining process and then reduce manufacturing scraps. Regarding sensors network design, we collect sensors related data covering machines behaviour (temperature, depressions, throughput, time, position, material fluidity, etc.); in-process product controls (quotations, product centricity, material thickness, etc.); and manufacturing environment (temperature, pressure, humidity). At the end of the manufacturing operations, additional quality control actions are performed through a 3D image processing (Open CV) (Figure 2 and Figure 3) to confirm the acceptance of the product quality comparing the theoretical tolerance values. The set of monitoring data are summarised in the following table (Table 1).

For risk management, regarding the history of

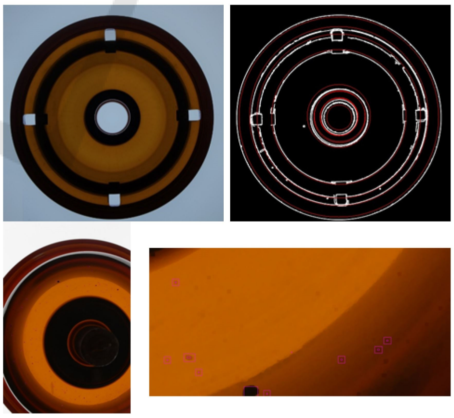

Figure 3: Image processing for plastic items quality control.

nonconformity, we identify and classify the critical transformation steps, specific machining tools, raw material transformation processes and human machining operations. The risk gravity is considered for the generation of quality control model. As verification rules for product quality are quite complex and need to be frequently adapted, we propose in this re-

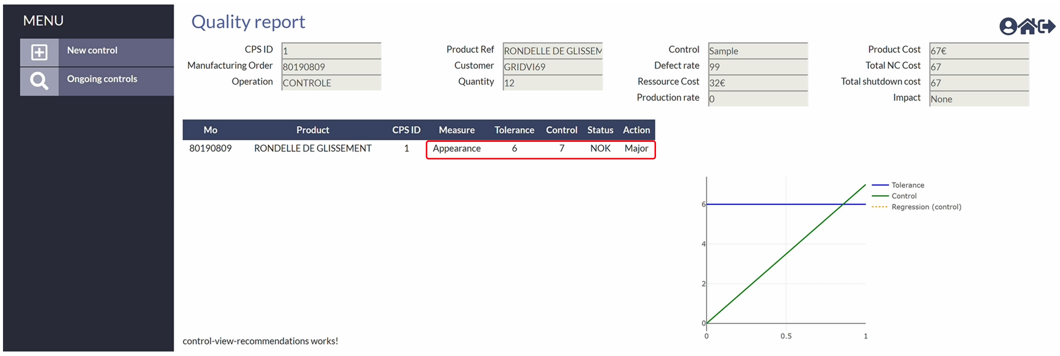

Figure 4: Quality control report.

search to adopt a machine learning approach built to automatically ingest new monitoring data related to product, production machines, environment, control, risk and resilience criteria. Our system follows a supervised approach, learning incrementally on the fly and detecting patterns in the training data to build predictive models. Adapted learning algorithms (KNN, LR, SVM, etc.) are experimented together to release the most adapted predictive model helping to evaluate the acceptance of detected defects. The following figure (Figure 4) illustrates the quality control report generated after each product inspection. The controlled product was rejected as the number of controls exceed the tolerance limit.

5 CONCLUSIONS AND FUTURE WORKS

We propose in this paper a global quality control approach covering the in-process and traditional quality control processes. We harvest a resilient network of sensors at the manufacturing work cell perimeter, and we propose a set of concepts helping to combine technical data (from sensors) with identified risks and resilience requirements. The proposed concepts are experimented to predict defect and control the quality of machined products in plastic industry. For the future work, we expect to increase the variety of the controlled products. It's about the consolidation of the Quality Control models repository to be able to upload the adequate quality control model when we start product machining. Uploaded model will be tuned through the new collected data and manufacturing events.

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