PhD Topic

XQuality: Explainable Quality Assurance and Diagnosis in Manufacturing Processes

Keywords: Semantic technologies, Ontologies, Knowledge Graphs, Explainable AI (XAI), Quality Assurance and Industry 4.0 (Quality 4.0).

Context

Industry 4.0 aims at improving the manufacturing and associated services through the digitalization and automation of manufacturing processes. A key characteristic of smart factories in Industry 4.0 is that assets and machines are equipped with sensors which collect data for effective equipment monitoring, transforming the traditional model of automation to a model of interconnected services. Increasingly complex products require increasingly complex and powerful production lines.

French and German manufacturing companies are known for their high-quality production and their orientation towards smart factories. Quality assurance and control of complex production systems is a major challenge and is further exacerbated by the shortage of skilled labour in this domain. Quality problems must be detected and eliminated quickly. When a quality problem is detected, it is necessary to quickly understand the multiple possible causes for it (which can sometimes be contradictory to each other) in order to propose the most appropriate corrective actions to return the manufacturing process to its normal operating mode.

The **XQuality project** is about researching hybrid and explainable AI approaches to help manufacturing companies implement intelligent and automated quality assurance. The project combines data-based machine learning, semantic technologies and expert knowledge to monitor and explain product and process quality targets in a company. The goal is to develop an AI-based system that will assist the staff in identifying the main causes of quality issues as early as possible, to achieve reliability engineering in the domain of manufacturing, thanks to the new quality assurance models.

Proposed methodology and objectives of these PhD works

Quality assurance (QA) and Industry 4.0 (Quality 4.0) [4] is the digital continuum of quality data combined with other data from sources such as manufacturing, machine sensors, supply management, and in-service across a product's life. Quality loss/defects need to be detected, explained and corrected at machine, production line, or fabric level. Causes for quality issues can be multiple and even contradictory to each other. For quality control or prediction, the techniques are focused on individual machines, like CNC [10], milling [7], drilling [11], etc. Basis for the analysis are time stamped data collected in the production line, coming from heterogeneous sources, such as sensors (measuring conditions, alarms, events), cameras (for visual quality control) and documents (including product specification and troubleshooting of the machines) must be integrated and interpreted. This is a challenging task as it requires the processing of heterogeneous data coming from different sources, with different temporal resolutions and different underlying meanings. Moreover, to create added value out of this information, it must be combined with data-based AI methods and domain and expert knowledge containing the resources (such as machines or processes) specification, the planning information and the quality requirements. The decision-making phase of the overall quality control will rely on innovative Reliability Engineering models, based on a hybrid AI approach (data-based and expert knowledge), to identify the ultimate situation that has provoked the detected quality loss.

Explainable Artificial Intelligence (XAI) [6] aims to generate automated explanations that are understandable to humans, which make the decisions made by AI systems in individual cases comprehensible and understandable to the user [1, 12, 9] . On the one hand, this makes an AI system more trustworthy and thus more acceptable to the user. Beyond purely ML approaches to explainability, semantics-based models of explainability have been proposed [3, 2, 8, 5]. XAI is a prerequisite for a later implementation in industrial practice and acceptance of the generated results in quality loss. It helps in the identification of the main cause in the event of a deterioration in quality in manufacturing and can thus also carry out manufacturing process optimisations independently, or supported by the user. This XAI-based quality loss analysis should be able to be applied to both structured data (sensor values and process data) and unstructured data (images of the manufacturing process) and is the basis for the overall quality loss remediation.

Figure 1 shows the framework of the overall **XQuality project**, with emphasis on the semantic enhanced representation layer that is a semantic representation of machines, events, quality issues and the behaviour of the production system associated with knowledge from data and experts, in order to generate an explainable diagnosis.

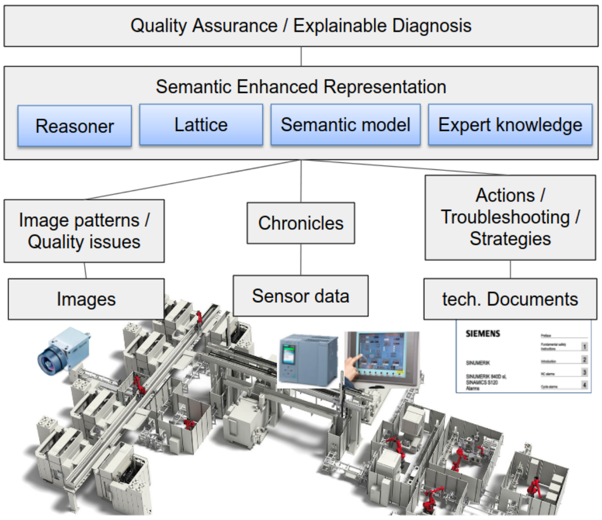

Figure 1: XQuality Framework

The overall objective of the **XQuality project** is to assist operators in manufacturing companies in understanding and mastering the quality assurance processes. It aims at detecting these quality issues in a production line but additionally: (i) to diagnose them using data mining approaches from sensor data, images and text; (ii) to understand their earliest causes; (iii) to propose actions plans based on a hybrid explainable approach with data and expert knowledge models.
The main expected outcomes of these PhD works are:

- Semantic description of machines, events and the behaviour of the system. It involves the creation of manufacturing process fingerprints based on process parameters relevant to quality issues.
- Theoretical contributions to the development of explainable models using hybrid AI approaches. Proposal of new semantic XAI approaches to explain quality issues in a manufacturing process using structured and unstructured data and domain and expert knowledge.
- Development of a hybrid and explainable reliability engineering model based on a semantic description of machines, events and the behaviour of the system; associating data and expert knowledge based models.

Environment

The PhD is fully funded for 3 years (part of the ANR-funded **XQuality project**) and will start in September 2023. The PhD student will be welcomed in the LITIS laboratory at INSA Rouen Normandie and the ICube laboratory at INSA Strasbourg, and supervised by Professor Cecilia Zanni-Merk (INSA Rouen Normandie) and Associate Professor Franco Giustozzi (INSA Strasbourg).

Candidate

We are looking for interested candidates with a Master (or engineer) degree (Bac+5 level) in Computer or Data Science. Skills in knowledge representation and reasoning, ontologies, knowledge graphs and knowledge-based systems will be more than appreciated.

How to apply

The interested candidates must send an email to Cecilia Zanni-Merk (cecilia.zanni-merk@insa-rouen.fr) and Franco Giustozzi (franco.giustozzi@insa-strasbourg.fr) **before May 31st** with the following documents:

- A CV,
- A cover letter (max. 1 page), including the applicant's motivation for applying and a brief explanation of their academic background,
- A transcript of the available grades for the current year and the past year,
- Recommenation letters or contact information of at least two referees.

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