Industrial Data Services for Quality Control in Smart Manufacturing – the i4Q Framework

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***Abstract*— This paper presents a new innovative framework to support smart manufacturing quality assurance. More specifically, the i4Q framework provides an IoT-based Reliable Industrial Data Services (RIDS), a complete suite consisting of 22 innovative Solutions, able to manage the huge amount of industrial data coming from cheap cost-effective, smart, and small size interconnected factory devices for supporting manufacturing online monitoring and control. The i4Q Framework guarantees data reliability with functions grouped into five basic capabilities around the data cycle: sensing, communication, computing infrastructure, storage, and analysis-optimization. i4Q RIDS includes simulation and optimization tools for manufacturing line continuous process qualification, quality diagnosis, reconfiguration and certification for ensuring high manufacturing efficiency, leading to an integrated approach to zero-defect manufacturing. This paper presents the main principles of the i4Q framework and the relevant industrial case studies on which it will be evaluated.**

Keywords*— Product Quality, Process Quality, Data Quality, Data Reliability, Blockchain, Virtual Sensors, Digital Twins, Process Simulation, Process Optimization, Zero-defect Manufacturing

I. INTRODUCTION

Manufacturing is a key sector for employment in the European Union generating three-quarters of Europe's exports [1] and more than 14% of European GDP [2]. The industrial sector is important to the EU economy and remains a driver of growth and employment. Industry provides added value through the transformation of materials into products. Although only roughly 1 in 10 enterprises in the EU is classified as manufacturing, the sector comprises 2 million companies and is responsible for 33 million jobs. Moreover, every new job in manufacturing results in the creation of between one half and 2 jobs in other sectors.

The manufacturing sector generated EUR 5.812 Billion of turnover and EUR 1.400 Billion of value added. By these measures, manufacturing was the second largest of the NACE sections within the EU-27's non-financial business economy in terms of its contribution to employment (21,4%) and the largest contributor to non-financial business economy value added, accounting for one quarter (26,6%) of the total. Furthermore, SMEs are the backbone of manufacturing industry in Europe. Micro, small and medium enterprises provide around 45% of the value added by manufacturing while they provide around 59 % of manufacturing employment. These important figures are complemented with the European Union Commission strategy that intends to expand industrial production in the EU from its current share of 15,5% of GDP to 20% by 2020. Resulting smart factories with high levels of digitalisation will be a key element for this new form of industrial production. Initiatives such as the German "Industry 4.0" with a total investment of EUR 40 Billion every year by 2020 [3] and a governmental fostering of close to EUR 500 Million are supporting the development of the required technologies.

Manufacturing companies are continuously facing the challenge of redesigning and adjusting their manufacturing systems to adapt their process to produce goods adapted to specific requirements and produced under the minimum required production rate, guaranteeing high quality and limiting the use of resources in order to reduce production costs. Therefore, reducing waste, scraps and defects, as well as production costs and lead times is crucial to increase productivity and hence, to pursuit manufacturing excellence. In this context, the implementation of zero defect strategies plays a decisive role. Addressing the above issues, this paper presents an innovative framework (i4Q) to support smart manufacturing quality assurance.

II. THE BACKGROUND

A. The Challenges

During the last decades several manufacturing operations and manufactured products quality optimisation methodologies and tools, such as the use of sensors and automated processes, have been implemented in European manufacturing companies with the aim of improving quality management and reduce variability on the manufacture of goods. Besides, and especially during the last decade, several R&D efforts have targeted on zero defect approaches with the purpose of developing solutions to improve performance of process control by incorporating enhanced quality control solutions. Nevertheless, current solutions show three major drawbacks that have not been solved.

- Data management: Thanks to the increase in the use of sensors, actuators and instruments, European manufacturing lines collect a huge amount of data, during the manufacturing process, which is very valuable for the improvement of quality in manufacturing but, for most of the European factories it is not possible to analyse the data generated in the process on a daily basis. At the same time the quality of these data is a crucial factor.

- Complexity of current solutions: Requiring heavy statistical and technology training and support, making them not accessible for SMEs. Now, users are demanding access to insights from advanced analytics, without requiring them to have IT or data science advanced skills. Most of current solutions lack of easy to use advanced data preparation, production reporting and advanced analytics and prediction.
- Dynamic behaviour of the manufacturing factories: Complex systems of diverse, connected, interdependent entities which need suitable modelling and simulation approaches and data fusion techniques to interpret the collected data

B. *Manufacturing Data Analytics*

Since the third Industrial Revolution, which was characterised by the emergence of the digital information age, that manufacturers all over the world are embracing the notion of convergence of the digital and physical worlds [4]. Mainly due to this convergence and to technological advances achieved throughout the last two decades, manufacturing-related data is being generated at exponentially growing rates [5]. Still, there are few manufacturing sectors that truly capitalize on such amount of collected data, by extracting meaningful insights for supporting improvements on their businesses, processes and products [6].

Recently, the application of Data Analytics to manufacturing data has been presented as a solution for the issue of capitalizing on ever-growing manufacturing data [7]. Manufacturing Data Analytics can be defined as the process of finding useful information from analysing manufacturing-generated raw data, whether for decision-making support or for optimisation of business and production processes, among other objectives [8], [9] present the main objectives for applying Big Data Analytics (BDA) in smart manufacturing. It is envisioned that future BDA applications will be able to assist enterprise managers to learn everything about what they did today and to predict what they will do tomorrow. This future vision is based on a taxonomy of data analytics approaches for manufacturing, which entails four types of analytics processes: descriptive, diagnostic, predictive and prescriptive analytics [5], [10].

Both descriptive and diagnostic analytics methods are reactive while predictive and prescriptive analytics approaches are proactive. Descriptive analytics is an exploratory analysis of historical data to tell what happened. During this stage, most of data mining and statistical methods can be used to reveal the data characteristics, recognise patterns and identify relationships of data objects. Diagnostic analytics is a deeper look at data to attempt to understand the causes of events and behaviours. The diagnostic analysis of machines and other equipment can help to identify the possible faults and predict the failures to reduce the machine down-times.

Predictive analytics mainly utilises historical data to anticipate the trends of data (i.e., what will occur in the future). Finally, prescriptive analytics extends the results of descriptive, diagnostic and predictive analytics to make the right decisions in order to achieve predicted outcomes. The prescriptive methods typically include simulation, decision-making, optimisation and reinforcement learning algorithms. Although the three first types of data analytics are not new research trends, the fourth, prescriptive analytics, is seen as a future challenge in Manufacturing Data Analytics [6], and is closely linked to simulation (digital twins) and optimisation.

C. *Manufacturing Data Collection*

Modern manufacturing produces high volumes of data [11] up to the point that the concept of "Smart Manufacturing" is itself tightly intertwined to that of data-driven manufacturing [4], allowing companies - for instance - to visualise, analyse and react to both collected and real-time (or near real-time) information, relevant to many areas of manufacturing, ranging from production to maintenance, order management and supply chain. Additionally, data can be used in periodic analysis and strategic/business planning.

As highlighted in various research - e.g. [12] - the quality of data plays a critical role in business applications under various aspects including performance, decision-making (management) and cooperation. As already highlighted by [13] it is of course important to define what 'data quality' actually means. In fact, there are several dimensions (and measures) related to the concept. In their book on Data Quality [12] the authors examine in great detail the dimensions of data quality, highlighting how literature does not always agree on the definitions of such dimensions and measurements.

Nonetheless, common attributes/measures defining a basic set of data quality attributes can be identified in the dimensions of *accuracy, completeness, consistency, timeliness*.

Accuracy, two types of accuracy can be defined, syntactic and semantic. The former essentially assesses how close a data value is to a set of values defined in a domain considered syntactically correct. The latter assesses closeness from a semantic point of view.

Completeness assesses the degree to which a given data collection includes data describing the corresponding set of real-world objects. In certain domains (especially databases), completeness has to do with the presence (and meaning) of null values, therefore some authors suggest that during quality assessment a Boolean value should be associated with a field.

Consistency assesses the adherence to semantic rules defined over a set of data i.e. answering the question: "are data consistent across the data sets?" and "are the data representing conflicting information?".

Currency is a time dimension which relates to how often the data is updated. Related time dimensions are *volatility* which represents how frequently data changes in time (e.g. a birth date has volatility equal to zero), and *timeliness* which specifies the currency of data with respect to a given task/usage e.g. data could be current, but still late for a certain usage.

Accessibility relates to the capability of users to access data within their own context, including physical status/functions, technologies and culture.

Additionally, domain ontologies are suggested as a tool to improve data quality management tasks. [14] reports several efforts to propose ontologies, semantics, and semantic web technologies within manufacturing and underlines how semantically rich descriptions can provide benefits in Industry 4.0 scenarios.

III. The Proposed Solution

i4Q is a complete solution, the i4Q RIDS (Reliable Industrial Data Services), integrating a set of i4Q Solutions, targeting the manufacturing sector and aimed at improving the digital manufacturing through more reliable and effective data. It is founded on a unified yet modular Framework, rooted in a consistent Reference Architecture which encompasses the following core layers: physical, network, middleware, database, and application. The Reference Architecture is based on current standards in manufacturing (e.g. IIRA, RAMI4.0, IDSA, and IMSA) and incorporates all fundamental *viewpoints* involved in the process: business, usage, functional and implementation. i4Q therefore aims to support the complete flow of industrial data, starting from data collection to data analysis, simulation and prediction. It provides solutions to ensure data quality, security and trustworthiness, especially tailored for manufacturing, such as blockchain-based data services and distributed storage.

i4Q also includes a set of services for data integration and fusion, data analytics and data distribution. Execution of AI workloads (including at the edge) is enabled and effectively managed through dedicated services which enable the dynamic deployment scenarios based on a cloud/edge architecture. Monitoring at various levels is provided in i4Q through scalable monitoring tools and the collected monitoring data are used for a variety of activities including resource monitoring and management, workload assignment, smart alerting, predictive failure and model (re)training.

Digital twins are extensively used, enabling full digitisation of the manufacturing process and providing simulation and modelling capabilities. Digital twins are used for process qualification - in particular to analyse how process parameters affect final product quality and obtain virtual sensors, as well as to explore potential upgrade actions and extend existing process data. Additionally, digital twins support quality diagnosis of the manufacturing line. Typical process qualification methods are improved in i4Q thanks to automated continuous process qualification and the use of real-time data.

In order to facilitate wide and agile deployment, i4Q adopts a modular, microservices-based approach, allowing the framework - and individual components - to be adapted and integrated in different manufacturing scenarios, for diverse companies and at varying maturity levels.

A. Goals

With i4Q RIDS, factories will be able to handle large amounts of data, achieving adequate levels of data accuracy, precision and traceability, using it for analysis and prediction as well as to optimise the process quality and product quality in manufacturing, leading to an integrated approach to zero-defect manufacturing.

i4Q Solutions efficiently collect the raw industrial data using cost-effective instruments and state-of-the-art communication protocols, guaranteeing data accuracy and precision, reliable traceability and time stamped data integrity through distributed ledger technology. i4Q provides simulation and optimisation tools for manufacturing line continuous process qualification, quality diagnosis, reconfiguration and certification for ensuring high manufacturing efficiency and optimal manufacturing quality.

Regarding data collection, the i4Q framework progress beyond the state-of-the-art by focusing on the prescriptive analytics challenge, which entails several smaller challenges, such as close-loop integration between data analytics and simulation processes (in order to bring simulation and digital twin models the closest to reality as possible and to capitalize on the insights gathered from such models) [5] and by leveraging data analytics workloads between edge and cloud computing (so as to implement an hybrid cloud/edge computing scheme, to not only exploit the strength of cloud computing to process the complicated tasks but also harness the benefit of edge computing in short latency, consequently obtaining the better performance).

B. Procedure

To illustrate how i4Q will work, a supposed scenario is stated below. The management of a manufacturing company in a value-added network decides to develop a successor model for one of its products. By implementing the i4Q RIDS, all data necessary for the production of the new product from the different internal and external sources of the production of the predecessor model is centralised (IoT), consolidated, subjected to automated pre-processing and made available in a scalable internal physical storage system or virtually in a cloud for further processing. Furthermore, i4Q data acquisition, preparation and storage processes assure data quality and neutrality at all times. The use of a blockchain-based data service ensures the reliability, trustworthiness and traceability of the existing data. A system containing multilayer cyber security features protects data supplied to the IoT-system. In order to use the full potential of i4Q for the development of a new process, data of previous production processes is needed. Through the monitoring of the company's production processes, a large number of the manufacturing parameters required for the production of the predecessor product are already available in the company's own databases.

Based on this already existing manufacturing data, i4Q QualiExplore checks the data reliability and enables the digital simulation of the production of the successor model by means of a digital twin. The bundling of all data from the different areas of development and production necessary for the manufacturing of the new product, in this virtual image of new production processes, enables a validation and visualisation of the production process to be developed. Critical production parameters and potential sources of error can be quickly identified, analysed and eliminated in the virtual model of the production using the i4Q Big Data Analytics Suite. In order to ensure the quality of the products in production, multivariate production parameters have to be converted into critical quality characteristics which will be used for inline quality assurance later on. Furthermore, the simulation model can be extended by virtual sensors to generate additional data and the effect of potential optimisation options of the production process can be explored. On the basis of the results of production simulation, the actual real production process with the corresponding production parameters required for manufacturing of high-quality products can be derived.

This procedure reduces the process development costs as well as the ramp-up time for the new process, since cost- and time-intensive tests to determine the necessary manufacturing parameters are largely eliminated. The i4Q RIDS includes an automated inline process qualification to evaluate the capability of the process to produce products that meet the quality requirements. Data from the pre-series process is used to evaluate the capability of the process. Once the capability has been proven, the start of production (SOP) can take place. After starting the process, the critical quality characteristics are continuously monitored.

The production parameters of all production units integrated in the process flow together in real time centrally in the i4Q data system and are prepared, and evaluated for analysis. Even minor deviations in production parameters relevant to quality features can be detected and localised by the real-time monitoring and automatic process analysis and a reconfiguration of the process can be performed. This prevents the production of low-quality products, reduces production down time through error localisation and possible failure costs. The digital twin of the process allows efficient and effective troubleshooting and intelligent reconfiguration of the corresponding production units with subsequent evaluation. The optimisation of the critical production parameters for reconfiguration of the production process will be performed in the virtual environment of the digital twin. After successful completion of the reconfiguration, a new process qualification with subsequent production release is carried out.

C. *Evaluation*

This section identifies the 6 industrial scenarios for i4Q coupled with a high-level user expectation of impact across different industrial activities, sectors and domains. The concrete industrial use cases introduced below will be implemented in 2021 and 2022 as part of i4Q to demonstrate the applicability and the impact of the project and its results in the market environment under real-world conditions. It should be noted, however, that i4Q will be designed for any industrial sector in highly complex inter- or intra-organisation scenarios, and not limited to the challenges of the pilot cases of the project.

The i4Q Project will deploy/validate the i4Q Solutions in pre-defined use cases which have been chosen for their complementary nature yet building upon some common themes. A total of 6 Pilots are envisioned, representing different Industrial Sectors and activities: White Goods, Wood Equipment, Metal Machining, Ceramics Pressing, Plastic Injection and Metal Equipment. All of them are representative of high-tech manufacturing sectors characterised by an increasing demand for high quality products and a need for factories digitisation and data reliability. In this regard, the selected i4Q pilots represent a very representative sample of industry. Furthermore, the six pilots belong to two different levels of the manufacturing process where the exploitation of data is instrumental to optimise the production's quality: machine tool providers, and production companies. Players in these two levels need to interact to tackle specific challenges related to quality monitoring, and process qualification. To gain a general vision of the i4Q Pilots and see their complementarity, they have been characterised by three main criteria: i) if the use case addresses the challenges in data reliability, data fusion and simulation, ii) the set of generic technologies to be worked on, and iii) the industrial and technical partners of the consortium that will be involved.

IV. Conclusions

i4Q framework provides a complete solution consisting of sustainable IoT-based Reliable Industrial Data Services (RIDS) able to manage the huge amount of industrial data coming from cost-effective, smart, and small size interconnected factory devices for supporting manufacturing online monitoring and control. The i4Q Framework guarantees data reliability with functions grouped into five basic capabilities around the data cycle: sensing, communication, computing infrastructure, storage, and analysis-optimisation; based on a microservice oriented architecture for the end users.

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