Transforming Quality Control in Manufacturing: An In-Depth Exploration of i4Q Solutions in the FACTOR Pilot Project

Miguel A. Mateo-Casalí[1], Pablo Rocamora [2], Alfredo Giménez[2], Ana Gómez González [3], Héctor Martín[3], Benjamin Mandler[4], Arcadio Garcia[5] and Raul Poler[1]

[1] Research Centre on Production Management and Engineering (CIGIP), Universitat Politècnica de València, Camino de Vera s/n, 46022, Valencia (Spain).
[2] Factor Ingeniería y Decoletaje, S.L., C/ Regadors 2 P.L. Campo Anibal 46530, Puçol, Valencia (Spain).
[3] IKERLAN Technology Research Centre, Basque Research and Technology Alliance (BRTA), Arrasate, Basque Country (Spain).
[4] IBM Research Lab1, Haifa University Campus, Haifa, 3498825, Israel
[5] EXOS Solutions, Camino de Vera s/n, 46022, Valencia (Spain).

Abstract

A far-reaching initiative is underway within the European Industrial Data Services for Quality Control in Smart Manufacturing (i4Q) project. This project creates 22 software solutions with the objective of improving the manufacturing process using data and Artificial Intelligence (AI). These solutions are designed to streamline manufacturing processes, emphasizing the fundamental aspects of quality assurance, operational efficiency, and seamless collaboration between manufacturing companies. The practical application of these solutions will be developed in manufacturing environments, allowing them to be tested and proven with accurate Pilot data. One of these pilots is Factor, a manufacturing company dedicated to metal machining and precision turning. This paper covers (i) the introduction of the pilot business process and the project solutions; (ii) the goal that i4Q aims to achieve by the implementation of some of the solutions in Factor; (iii) information on the factory's current Key Performance Indicators after the introduction of the solutions.

Keywords

Industry 4.0, Smart Manufacturing, Quality Control, Edge Computing.

1. Introduction

This workshop is contextualized on the European Project Industrial Data Services for Quality Control in Smart Manufacturing (i4Q) [1]. To this end, i4Q aims to provide an IoT-based Reliable Industrial Data Services (RIDS), a complete suite comprising 22 solutions for assuring data quality, product quality, and manufacturing process quality, aiming at zero-defect manufacturing [2]. This workshop will present different solutions applied to the i4Q Factor Pilot project.

FACTOR *Ingeniería y Decoletaje S.L* [3] is a Valencia-based manufacturing firm in Spain specializing in metal machining and precision turning. The company serves highly regulated industries such as aeronautics, automotive, and medical. The primary objective of FACTOR is to uphold product quality, preventing defects in production that could lead to cost reductions, enhanced efficiency, and increased customer satisfaction. Various factors in computerized numerical control

12th International Conference on Interoperability for Enterprise Systems and Applications (I-ESA24), April 10th-12th, 2024, Chania, Crete, Greece
EMAIL: mmateo@cigip.upv.es (MA. Mateo-Casalí); p.rocamora@factorsl.es (P. Rocamora); alfredo@factorsl.es (A. Giménez); ana.gomez@ikerlan.es (A. Gómez González); hmartin@ikerlan.es (H. Martín); mandler@il.ibm.com (B. Mandler); arcadio.garcia@exos-solutions.com (A. García); rpoler@cigip.upv.es (R. Poler) 0000-0001-5086-9378 (MA. Mateo-Casalí);
ORCID: 0000-0001-5086-9378 (MA. Mateo-Casalí); 0009-0006-0095-9256 (P. Rocamora); XXXX-XXXX-XXXX-XXXX (A. Giménez); 0000-0001-5720-0183 (A. Gómez González); 0000-0001-5471-1017 (H. Martín); 0009-0003-2456-7431 (B. Mandler);); 0000-0003-4475-6371 (R. Poler)

(CNC) machining influence manufactured parts' dimensional and aesthetic attributes. Consequently, ensuring the quality of these parts necessitates real-time quality control measures during the production process. However, conventional in-process quality control is intricate, time-consuming, and involves costly measuring equipment. Furthermore, it is not foolproof, leading to material wastage, and the data collected is often confined to a specific production run. FACTOR aims to leverage the i4Q RIDS to implement a comprehensive 100% in-process quality control system for manufacturing. This innovative approach involves utilizing the data obtained to scrutinize the current production and anticipate and address potential manufacturing issues through algorithmic analysis, maximizing efficiency and minimizing defects.

2. The Pilot

The ability of manufacturing companies to respond to the market is challenged by the increasing frequency of new product launches, shortening product life cycles, modifications to existing products, government regulatory changes, substantial variations in product demand, and technological evolutions in processes [4, 5]. In this scenario, manufacturing systems must exhibit the agility to adapt quickly to these market requirements, producing high-quality products while efficiently managing operating costs [6].

FACTOR aims to achieve significant results by implementing i4Q solutions. First, it seeks to eliminate defective parts, thus increasing the quality ratio in production. It also aims to eliminate machine downtime, extending the time machines produce final products efficiently. In addition, it aims to improve Overall Equipment Effectiveness (OEE), a measure that involves the quality ratio, availability, and effectiveness. Defining Key Performance Indicators (KPIs) supports this set of objectives.

OEE	Quality Ratio (**QR**) * Availability (**AVA**) * Effectiveness (**EFF**)
QR (%)	number of Quality Parts **(GQ)** / total Produced Quantity **(PQ)**
AVA	Actual Production Time **(APT)** / Planned Busy Time **(PBT)**
EFF	(Planned Runtime per Item **(PRI)** * PQ) / APT

Table 1. KPIs definition to monitor i4Q results.

The assessment of factory efficiency is carried out by OEE, whose calculation involves the product of the quality ratio, availability, and efficiency (see Table 1). The quality ratio, on the one hand, reflects the ratio between the number of good parts and total production. In other words, it indicates how many parts without defects are ready for delivery relative to the total produced, providing an indicator of waste. On the other hand, availability reveals the relationship between the actual machine production time and the planned occupancy time for a unit of work. Finally, Effectiveness is defined as the ratio between the planned target and actual cycles, expressed as the planned run time per item multiplied by the quantity produced divided by the actual production time.

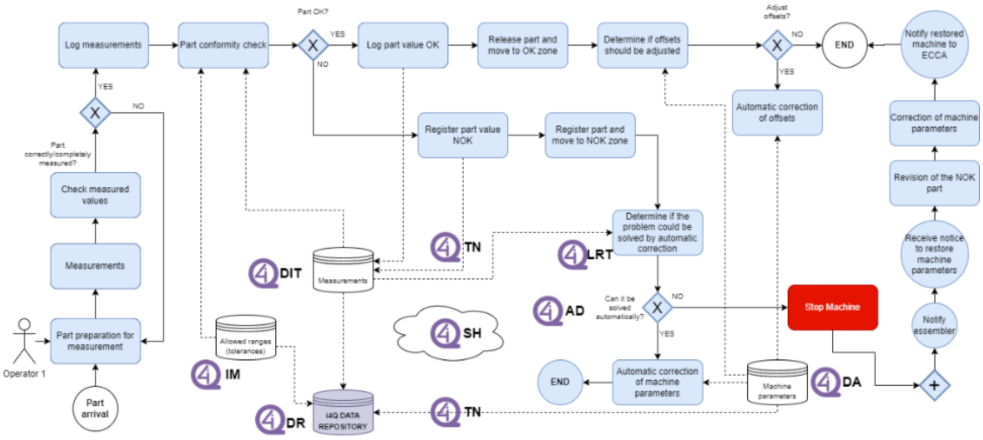

Figure 1. Business Process – In line Product Quality Control

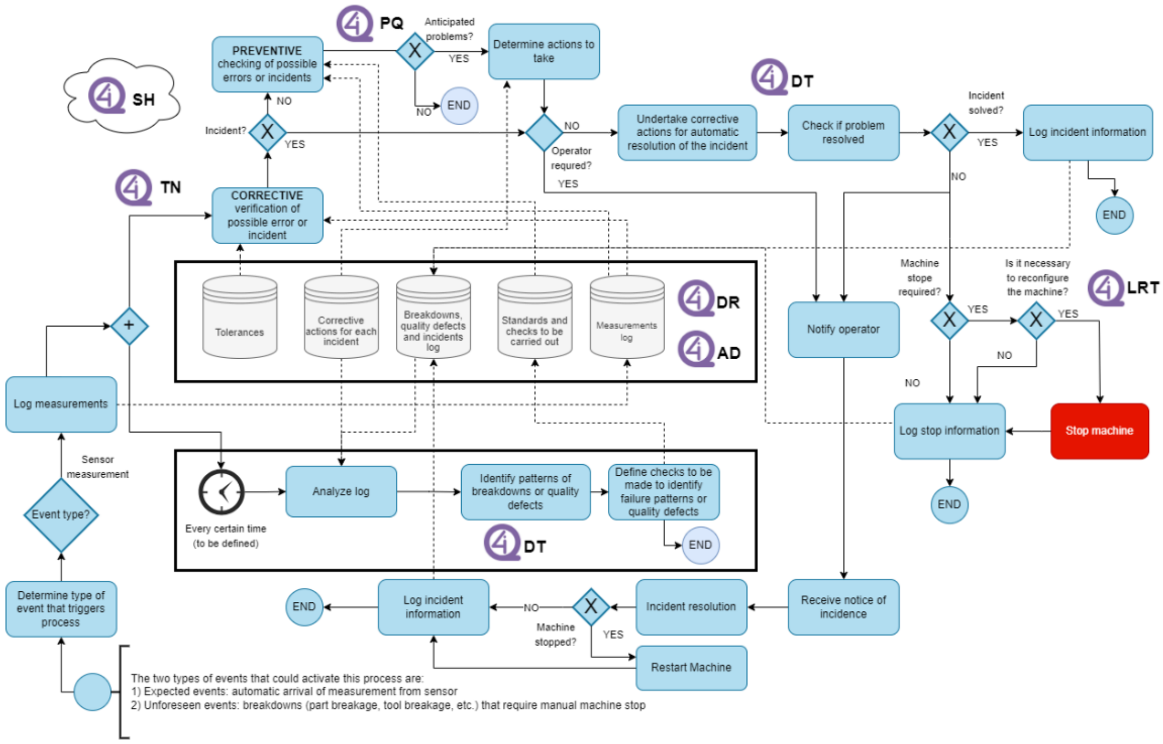

Figure 2. Business Process – Machine adjustments in the machining process

With FACTOR's primary objective in mind, different i4Q solutions have been implemented to improve OEE. This set of solutions has been implemented to cover two business processes. These two business processes are in-line product quality control (Figure 1) and Machine adjustments in the machining process (Figure 2).

The first business process (Figure 1) aims to ensure the quality of the produced parts, ensuring that the geometry of the parts fits the tolerances of the quality guidelines. Since the physical variables of the manufacturing process influence the production outcome, most defects can be avoided by maintaining the process stable. When a part is measured, the system analyses the health of the measurements, determining if the values are aligned with the expected results.

If the accuracy of the measurements is not correct, the part will be placed again in the place to be measured, returning to the start of the process. If the accuracy is correct, the measurements will be logged even though they have not been analysed in terms of quality. This will help to determine the production parameters that influence the poor quality of the part. Once the results are stored, the system should check if the part is in line with the quality guideline and three scenarios can occur (Table 2).

Scenario	Description
Completely OK	Since the geometrical values are exactly the nominal values required by the customer, the part will be considered an OK part, and the manufacturing process will continue.
Not completely OK	It enters the customer tolerances.
Not OK	If the part does not enter the tolerances, the process will stop.

Table 2. Quality results

Regarding the second business process, monitoring the status of the machining process is key to enabling a predictive analysis of the process behaviour, allowing the optimisation of the process to avoid inefficiencies by changing the relevant parameters that influence faults before the error occurs (Figure 2). In the beginning, which type of event triggers the process is determined: a periodic sensor measurement or a failure in the process. If it is a periodic sensor measurement, the values should be logged, and the process qualification starts in both corrective and preventive branches. The corrective actions are the first process qualification and are based on the determination of whether there is an incident happening online in the manufacturing process. If it is an incident, the system should check if an operator is required to solve it. If there are no problems in the manufacturing process, the system should perform a preventive process, checking the possibility of future problems, anticipating them through AI, and providing corrective actions. Both approaches end up with the conclusion of whether an operator is required to solve the problem, providing the corrective actions for solving the incident and checking if the problem has been solved. Finally, the system should also determine if the machine should be stopped if there are no possible corrective actions to undertake that would avoid the problem.

3. i4Q Solutions

3.1. i4Q Digital Twin Tool

The i4Q Digital Twin (i4QDT) is a toolkit for building models of a manufacturing asset/plant based on production/machine data and for launching different simulations that represent the real behaviour of the system without physically interacting with it. The i4QDT is comprised of three main software packages: physics-based back end, data-driven back end and user interface front-end. The physics-based workflow makes use of Functional Mock-up Units (FMU) that have been compiled from different modelling languages like Modelica, which are component-oriented and based on a set of equations defining the physics behaviour of the system. The data-driven implementation, corresponds to machine learning methods, comprising data-driven machine learning techniques, which are highly promising since a model learns critical insights directly and automatically from the given datasets.

For the FACTOR pilot project, the first intended approach was to develop a physics-based model for simulating one of the machining processes involved in the manufacturing of the different pieces that are part of the FACTOR business. Nevertheless, due to the level of complexity of trying to obtain an accurate mathematical representation of the physical behaviour of the machine, and the high variability between the different pieces manufactured by FACTOR, a data-driven approach for piece quality prediction was selected as the final solution to be integrated in the second business process presented in the previous section.

The data-driven model has been developed thanks to the data collecting system implemented by FACTOR during the project, and the historical databases provided both with the processing variables of their Nakamura machines and the different final piece dimensions registered by their quality department. The machine variables selected for representing the process were obtained from the database stored by the Nakamura, and comprise inputs such as the spindle motor speed, the cutting time and the temperature of the machine. For the piece quality results a compromise was made, as there were many different dimensions and for the training of the model a specific target variable was needed. To do just that, a global quality variable has been deducted along with FACTOR: a number representing, from all the different dimensions of the piece, how many of them are out of the accepting ranges. This allows the user to easily conclude an accepting criterion for the marketing of the piece based on the results of the prediction model.

One of the main challenges faced during the development of the quality predicting model was the need to temporarily correlate the processing variable data with the quality results. A specific algorithm can find a distinguishing pattern that accurately represents the beginning and ending of the machining process cycles. Along with the historical data, the i4QDT tool can train a model that, for a given set of processing variables, is able to obtain the expected quality of the manufactured piece, without the need of measuring it, thus allowing FACTOR to obtain conclusions of the best manufacturing conditions for avoiding piece faults and consequently increasing efficiency.

3.2. i4Q AI Workloads on edge Computing and Line Reconfiguration Toolkit

The i4Q Edge Workloads Placement and Deployment (i4QEW) is a toolkit for managing, monitoring, and running AI workloads on edge computing environments, as prevalent in manufacturing facilities. This solution provides interfaces and capabilities for managing the entire life cycle of workloads on different industrial devices, including running efficiently on edge, providing placement and deployment, and allowing the possibility to deploy Algorithms as a Service (AaaS).

Edge computing is establishing itself as the architecture of choice for many industries across many use cases; thus, forward-looking algorithms and systems must be devised. AI workloads at the edge are later used by the analysis components to run their inference close to the data sources. Target deployment environments may be heterogeneous and dynamic; thus, deployment must consider various criteria. The environment is dynamic; thus, re-deployment of the entire workload or adapting the underlying model may be required while the workload continues.

Deployment shall be based on well-known orchestrators, such as Kubernetes. Edge environments pose different challenges due to scale, heterogeneity, connectivity, and wide distribution, among other factors. Thus, using policy-based mechanisms, our solutions enable automatic decisions, such as target deployment. These mechanisms enable managing the end-to-end lifecycle at the edge without intervention from anyone. By processing data close to the source, the latency of the computational response is reduced. In addition, network bandwidth is conserved, which doubles as a first line of defense to address big data challenges by processing data locally as much as possible rather than serving as a conduit for all data to be transmitted to the cloud and processed there. Security and privacy are also addressed by maintaining and processing information locally, without outsourcing or sending it to the cloud or a central data center. Such an architecture can also be beneficial for complying with data-related regulations, such as restrictions on data storage and processing locations as this architecture allows working in a disconnected mode.

In the FACTOR pilot project, the i4QEW solution is used to manage the lifecycle of workloads and AI models. These AI models are prepared by the i4Q Manufacturing Line Reconfiguration Toolkit (i4QLRT) solution. The i4QLRT is a collection of optimization microservices that use simulation to evaluate different possible scenarios and propose changes to manufacturing line configuration parameters to achieve improved quality objectives, both solutions are combined within the FACTOR business process. The LRT is used for the Production Line Quality Control seen above. This solution aims to increase productivity and reduce the efforts for manufacturing line reconfiguration through AI.

The i4QLRT solution consists of a set of analytical components (e.g. optimization algorithms and machine learning models) to solve known optimization problems in the field of manufacturing process quality and find the optimal configuration for manufacturing line modules and parameters. This solution uses i4QEW to deploy a new version. When a new version of the algorithm appears, i4QEW will ensure that the new version is deployed to all intended clusters. This mechanism can support the handling of any K8s, K3s or Minikube. Thus, we support the GitOps-based mode of operation, where the point of interaction between the AI application developer and the solution is achieved through GIT. There is tight integration between AI model lifecycle management and AI workloads using these models. Thanks to this functionality between the two solutions, FACTOR can update the model to be deployed every time a part to be manufactured is changed.

In conclusion, the i4QEW and i4QLRT solutions are a comprehensive and forward-looking approach to managing AI workloads in edge computing environments, especially beneficial in manufacturing. The FACTOR pilot project is a practical test of the effectiveness of these tools in improving the productivity and adaptability of manufacturing processes.

4. Results and Conclusions

The implementation of i4Q solutions in the FACTOR pilot project has shown early signs of improvement in manufacturing efficiency and quality control. The focus is on two key areas: online quality control and machine adjustments in the machining process, with the overall goal of enhancing Overall Equipment Effectiveness (OEE). In online quality control, the system has focused on ensuring the quality of produced parts by maintaining stable manufacturing processes. The online control system evaluates geometric values, comparing them to quality guidelines. This approach ensures that only parts meeting quality standards continue in the manufacturing process, minimizing defects and waste.

The second process, related to machine adjustments in the machining process, involves monitoring the process state to enable predictive analysis and optimization. Two branches are followed, corrective and preventive, based on triggers such as periodic sensor measurements or process failures, accompanying the Zero Defects paradigm: (i) Corrective actions involve identifying incidents and determining if operator intervention is required. (ii) Preventive measures use artificial intelligence to anticipate potential problems, providing corrective actions to avoid issues in advance.

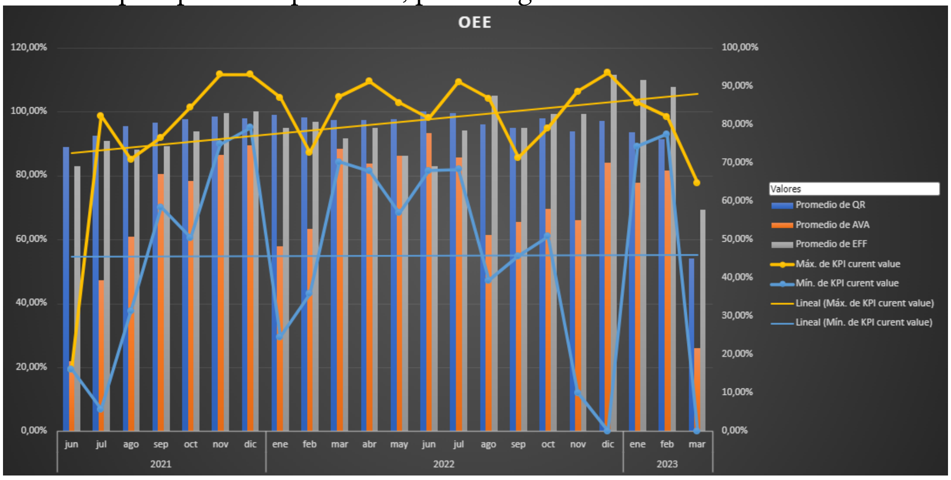

Figure 3. OEE FACTOR

The implemented i4Q solutions, such as the i4Q Digital Twin (i4QDT), are essential for quality prediction. However, at the project's outset, a physics-based model for machining processes was considered, but complexity led to adopting a data-driven approach. Using data collected by FACTOR, the model predicts part quality based on processing variables and historical databases. On the other hand, the collaboration between artificial intelligence workload solutions at the edge computing and the manufacturing line reconfiguration tool (i4QEW and i4QLRT) proved crucial for efficiently managing AI workloads and optimizing manufacturing line configurations. These solutions, employed in the FACTOR pilot project, represent a cutting-edge approach to artificial intelligence in manufacturing.

The definition of KPIs, including Overall Equipment Effectiveness, Quality Ratio, Availability, and Efficiency, has been used to assess i4Q results. By monitoring these metrics, FACTOR aims to eliminate defective parts, reduce machine downtime, and improve OEE.

Acknowledgements

The research leading to these results is part of the i4Q project that has received funding from the European Union’s Horizon 2020 Research and Innovation Programme, under Grant Agreement No 958205.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

References

[1] Industrial Data Services for Quality Control in Smart Manufacturing (2022) European Commision Project Nº Grant 958205 https://www.i4q-project.eu/

[2] Poler, R., Karakostas, A., Vrochidis, S., Marguglio, A., Gálvez-Settier, S., Figueiras, P., Gómez-González, A., Mandler, B., Wellsandt, S., Trevino, R. and Bassoumi, S., 2021, June. An IoT-based Reliable Industrial Data Services for Manufacturing Quality Control. In 2021 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC) (pp. 1-8). IEEE.

[3] Factor Ingeniería y Decoletaje (2022) https://factorsl.es/. Date accessed: 2023/12/22

[4] Koren, Y., U. Heisel, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, and H. Van Brussel. Reconfigurable manufacturing systems. CIRP Annals - Manufacturing Technology 48, 527–540 (1999).
[5] Koren, Y., X. Gu, and W. Guo. Reconfigurable manufacturing systems: Principles, design, and future trends. Frontiers of Mechanical Engineering 13, 121–136 (2017).
[6] Maganha, I., C. Silva, and L. M. D. F. Ferreira. The layout design in reconfigurable manufacturing systems: a literature review. International Journal of Advanced Manufacturing Technology 105, 683–700 (2019).