Manufacturing Line Qualification and Reconfiguration to Improve the Manufacturing Outcomes

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Abstract
Increased consumerism and the competitiveness of the global market have led to more stringent requirements in terms of product quality and manufacturing lines. The i4Q European project's Rapid Manufacturing Line Qualification and Reconfiguration set of solutions aims to develop new and improved strategies and methods for process qualification, process reconfiguration and optimization using existing manufacturing data and intelligent algorithms. The set of solutions provides manufacturing lines' diagnosis and prescription, process capacity forecasting, manufacturing line reconfiguration propositions, and data quality certifications and audit procedures. With this information, plant managers can make the required changes to the plant to improve manufacturing products' quality, machines' life cycle, plants' productivity and so on.

Keywords
i4Q, machine learning, smart manufacturing, process qualification, diagnosis and prognosis, digital twin, manufacturing line reconfiguration.

1. Introduction

Economic globalization and increased consumption in society have caused companies to need to optimize and improve production processes. This has resulted in increased competitiveness in the global market and the need for stricter requirements in terms of product quality and manufacturing lines [1]. To meet these stringent requirements, production line inefficiency and hidden loss must be detected and eliminated [2]. Currently, those actions are carried out through technological advances, such as sensors, machine data collection systems, data processing, application of analytical solutions and control systems. These methods and technologies have provided plant managers with the necessary tools to improve and optimize manufacturing lines by monitoring and controlling the state of machines. Despite market needs and technological advances, researchers and manufacturing professionals have struggled to detect the main cause of production lines' inefficiencies and to determine the necessary improvements to increase productivity.

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As noted by [3], any robust metric of a plant should be characterized by four features:

- Inclusiveness: the capacity to account for all pertinent aspects.
- Universality: the capacity of being compared under various operating conditions.
- Measurability: the capacity to measure data analytically.
- Consistency: the capacity to be inherent to all organizational goals.

However, both throughput and utilization lack inclusiveness as they only account for a portion of the manufacturing system performance. Additionally, the effectiveness of a plant depends on the way it uses equipment, material, men/women and methods, which cannot be easily measured [2]. Machines lack consistency, as they are programmed with the main goal in mind but neglect other secondary goals (e.g. electric consumption optimization). And machines' sensors lack universality, as the gathered data is usually tied to a specific operating condition.

2. Rapid manufacturing line qualification and reconfiguration

In the i4Q European project [4], the Rapid Manufacturing Line Qualification and Reconfiguration set of solutions aim to develop new and improved strategies and methods for process qualification as well as process reconfiguration and optimization through currently used manufacturing data and smart algorithms.

This set of solutions considers the particularities of the final process, adapting the available algorithms when needed. Furthermore, it considers the format in which the data may be obtained from the system, such as newly added sensors, readily available legacy data, or virtual sensors. A breakthrough of this work package lies in the use of the Digital Twin (DT) to:

i) Analyze the effect of process parameters on the final product quality.
ii) Obtain virtual sensors that extend available process data.
iii) Explore potential upgrade actions on the system.

These solutions (**Figure *1***) address the following topics:

i) Continuous process qualification to determine that outputs are within limits (PQ).
ii) Diagnosis strategies to detect cause of defect and recommend rapid corrective actions (QD).
iii) Simulation to guide preventive actions (PA).
iv) Optimization to reconfigure the production line (LRT).
v) Process and data certification based on reliable collected data (LCP).

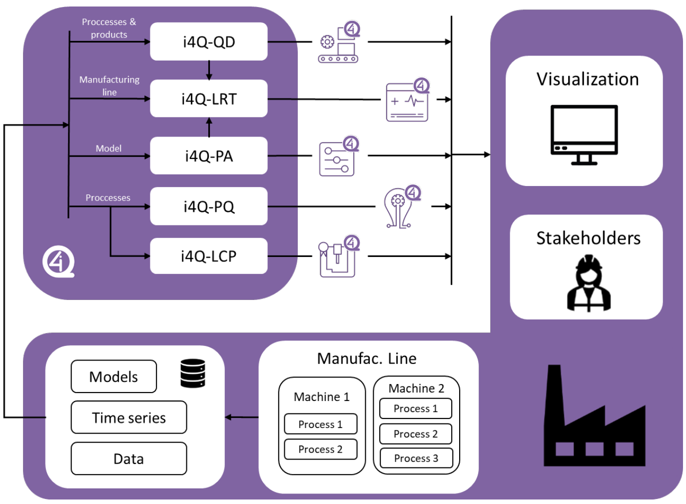

Figure 1: Rapid Manufacturing Line Qualification and Reconfiguration set of solution's diagram

2.1 Manufacturing line continuous process qualification

Continuously evaluating manufacturing processes is a common procedure to describe the capabilities of machinery in manufacturing industries. Therefore, multiple descriptive indices like process potential (C_p) and process performance (C_{pk}) [5] are calculated from samples to assess manufactured products in relation to a distinct quality feature. Maintaining this evaluation over time allows interpretations about process quality. To achieve this information, it is sufficient for the evaluation to assess a measurable quality feature concerning its numerical characteristics.

Furthermore, upper and lower tolerance levels are introduced by the process owners to define hard limits once the process is not in the desired quality range. This procedure is described in literature as statistical process control (SPC) [6]. In spite of the broad industrial application of the SPC, describing samples does not allow a real-time evaluation of desired process capabilities. In addition, non-normal distributions of the chosen samples or multi-stage manufacturing processes decrease the interpretation of the process and its performance [7]. To overcome this problem, the continuous line qualification (i4QPQ) is developed.

i4QPQ as software solution is providing three main services for process owners as microservice. It uses sensor data from manufacturing machines for its calculations:

1. Continuously evaluating process parameter C_{pk}: reading real-time data streams and presenting them over specified time range or product quantity transformed to non-normality performance index. Furthermore, single parameters can be adjusted by inserting them in a sidebar to create personalized analysis.
2. Indication of distribution characteristics: to inform the process owner about the distribution over the specified time range or product quantity, a distribution plot and the highlighted confidence interval of the last number of chosen products is displayed.
3. Capacity forecast and forecast accuracy: as information about the chosen time range into the future, a forecast about the process capacity is made concerning the current conditions of the machine. Additionally, the evaluation criteria of the forecast algorithm are provided to leave the decision about further actions in the process owners' responsibility.

Conclusively, the i4QPQ application is a customer centric and user-friendly software tool, which allows the interpretation of current and future process capability. Additionally, information about the current process status and its distribution are facilitating machine ramp-up and condition monitoring.

2.2 Manufacturing line quality diagnosis and smart alerting

The rapid quality diagnosis solution (i4QQD) is a microservice aiming to provide an efficient rapid diagnosis on possible causes of failures, on manufactured products quality, and on manufacturing process conditions. Specifically, i4QQD incorporates intelligent techniques to improve the final product quality by applying state-of-the-art Machine Learning (ML) techniques on industrial sensor signals [8]. Moreover, it conducts advanced causality analysis on machine parameters and on manufacturing conditions to infer the most influencing parameters. This mechanism is crucial since usually complex relationships and erratic dynamics govern industrial data, while exact patterns of signals evolution through time are not profound and latent factors affecting the overall manufacturing process cannot be directly detected by a human operator.

i4QQD key advantage is that instead of simply applying traditional ML algorithms, it reveals the laws that industrial data may obey, by explicitly modeling their trends, discontinuities, interdependencies, and interactions with respect to causation. The analysis results are provided i4QLRT (described below) to optimally reconfigure system parameters, and to take corrective actions if a problem is detected. Consequently, this process reaches three major goals towards zero-defect manufacturing: i) it reduces waste and cost, ii) it eliminates defects, and iii) it optimizes the overall production quality. Classification and regression are the fundamental ML approaches applied by i4QQD. The first one is applied in cases where the objective is to predict the class of given industrial data (e.g., chatter detection in computer numerical control (CNC) machining industries), while the second one is applied in cases where the objective is to anticipate estimations for future values of a certain variable (e.g., surface roughness prediction in CNC machining industries), For classification tasks, tree-based learning algorithms are deployed (e.g., gradient boosting frameworks). For regression tasks, recurrent neural networks are utilized (e.g., long-short-term memory neural networks, bi-directional long-short-term memory neural networks, gated recurrent units) [9]. Granger causality analysis is applied to detect the most influencing parameters affecting a manufacturing process and Kalman filtering and Markov Chain Monte Carlo techniques model the dynamics governing the sensor signals.

2.3 Simulation and optimization for smart manufacturing line reconfiguration prescription

Even the simplest models contain a significant number of internal parameters (for instance, the mass, stiffness, thermal conduction, and so on). These parameters are all correlated, hence changing the value of those parameters have a great impact on the model's behaviour. This complicates the analytical design of an optimum and robust system, and the analytical prediction of the effect of parameters' variation due to materials wear, vibration or other disturbances on the model's behaviour.

The prescriptive analysis tool (i4QPA) was created to deal with these issues. The i4QPA is a simulation, optimization and prescription tool. The main objective of this solution is to prescribe the optimum system configuration according to an evaluation function, being a configuration of a specific model's parameters' values data frame, and the system any DT model. To obtain the optimum configuration of a system, the i4QPA creates a model configurations data frame where every line represents a possible configuration of the model. Then the i4QPA conducts multiple simulations (one simulation per configuration), evaluates those simulations results and ranks them according to the selected evaluation function. Finally, the i4QPA prescribes the winning simulation's configuration.

The i4QPA solution is a user-friendly application in which the user can select the model, the parameters to vary, the evaluation function and the model's input data. Therefore, the solution requires a model and input time-series database (DB). Following the models/DTs standards, the i4QPA expects an FMU type model as model input, which is read and processed with a variation of the "FMPy" library.

Regarding other solutions, the i4QPA may give input to the i4QLRT (described below) and can be supported by the i4Q Analytical Dashboard, a data visualization solution. The communication between solutions is done through REST APIs.

2.4 Manufacturing line reconfiguration

The manufacturing line reconfiguration solution (i4QLRT) proposes changes to manufacturing systems' configuration parameters to achieve improved quality targets. This is done through a collection of simulation-based optimisation microservices that evaluate different possible scenarios, thereby increasing productivity and reducing manufacturing line reconfiguration efforts through Artificial Intelligence (e.g., optimisation algorithms, ML models). The solution can be used in the cloud or deployed on-premises, with sensor data from the manufacturing process as input and operational data as output (e.g., configuration parameters and actuation commands); it will optimise the manufacturing line with the best available set of parameters.

This solution is therefore based on optimisation algorithms developed in Python and deployed through a container (e.g., Docker) that exposes its main functions (metadata description and input/output configuration) as REST interfaces and provides access to data services (messaging, storage). It offers ready-to-use optimisation functions for business processes, data pipelines or applications. In this sense, the main architecture building blocks (ABBs) identified are the set of algorithms implemented in Python and the REST wrapper that facilitates deployment and integration into data pipelines and workflows. The wrapper must implement the client libraries to connect to the i4Q data services and DT APIs and must be deployable at the edge and manageable as an AI workload.

As microservices are deployed in Docker containers, they do not have strict hardware requirements, although they can benefit from GPU acceleration. Security, governance and management capabilities are delegated to external services through integrations using standard technologies (e.g., OAuth, certificates, RBAC). The i4Q^{LRT} software has interfaces to integrate into data pipelines (e.g., messaging, REST APIs, gRPC, OpenAPI). i4QLRT has no strict dependencies, and it is interoperable with other i4Q solutions such us, i4Q Digital Twin, i4Q Services for Data Analytics, i4Q Big Data Analytics Suite, i4Q Edge Workloads Placement and Deployment.

2.5 Certification and audit procedure

The i4Q Line Data Certification Procedure (i4QLCP) is a digitized certification and audit procedure to ensure data quality for reliable use of all related i4Q solutions. The solution provides a digital workflow for an audit procedure which can be conducted on manufacturing resources, e.g., machine, cell or manufacturing line. The workflow contains all essential steps in a logical sequence of activities which need to be performed to ensure high level data quality throughout the complete data generation process. These activities include auditing manufacturing resources for data generation (e.g., sensors, controls, software), using calibration devices, and performing tests. Furthermore, the procedure provides additional information to users, like shopfloor workers, process owners, and auditors, in the form of definitions and vocabulary, frame and application areas, prerequisites, planning, implementation, controlling, improvement and documentation of data-driven qualification, reconfiguration, applicable standards, and quality control.

The audit procedure works as a guideline and introduces gates that represent predefined milestones. For each milestone, the fulfilment of all requirements, necessary criteria, or activities is needed to allow the user to proceed to the next phase of the procedure. This is achieved, e.g., by uploading a digital signed document or report by the responsible user to a DB. To facilitate completion of the individual milestones, the procedure also contains relevant information in the form of instructions, references to relevant standards and internal company documents. After each gate is passed successfully, the software will provide a digital certificate. The complete documentation is stored on a secured and access-restricted DB with user identification. By accessing the secure DB, auditors are able to find all necessary documentation for each performed activity. Recertification procedures are simplified and less time consuming, as are all activities for audit preparation.

This procedure will complement already existing quality certifications by introducing manufacturing process data quality as a factor that needs to be considered in future audits.

3. Conclusions

The Rapid Manufacturing Line Qualification and Reconfiguration set of solutions aims to develop new and improved strategies and methods for process qualification, process reconfiguration, and optimization using existing manufacturing data and smart algorithms. The solutions are the following:

- The i4QPQ continuously evaluates manufacturing processes checking if outputs over time are within limits and forecasting process capacity.
- The i4QQD is a microservice aiming to provide efficient rapid diagnosis on possible causes of failures, on manufactured products quality, and on manufacturing process conditions.
- The i4QPA is a DT/model simulation, optimization and prescription tool.
- The i4QLRT proposes changes to manufacturing systems' configuration parameters to achieve quality targets.
- The i4QLCP is a digitized certification and audit procedure to ensure data quality for reliable use of all related i4Q solutions.

All the solutions as a whole give the user the tools to analyze and correct all manufacturing line aspects, from sensors, to processes, machines and manufacturing lines, fulfilling to a large extent Beamon's [3] inclusiveness metric. Moreover, the solutions carry out a wide range of actions, from predictions, to diagnosis, simulations, prescriptions, optimizations, qualifications, and so on. Actions that add the Beamon's metric of consistency to any manufacturing line, as the more information a company has, the better decisions the company carries out, and so a wider range of organizational goals can be fulfilled.

The PA and LRT carry out simulations under various conditions in order to obtain the optimum model or manufacturing line configuration, which would check the Beamon's universality metric.

And last, but not least, the measurability metric if fulfilled by the PQ, QD and LCP, as they analyze and check multiples aspects of sensors' or models outputs' signals.

These solutions altogether, provide manufacturing line managers with the tools to obtain all the robust metrics defined by Beamon [3]. Therefore, managers have all the required information to make the best decisions and changes to the manufacturing line, from the smallest internal process of the manufacturing line to the whole configuration of the manufacturing line, which would improve the production, the quality of the manufactured products and the machines' life cycle.

As for future research lines, every solution or software have its own future research line. The i4QPQ will be improved by implementing continuous evaluation criteria assessment for machine learning models and comparing the evaluation criteria of multiple forecasting algorithms and their outputs. The i4QQD's future work will be focused in adopting Transfer Learning techniques to combine the abilities of various models and enhance the performance of the i4QQD, in exploiting clustering techniques to address the frequent issue of unlabeled data, and in adapting Deep Neural Networks to classification-related tasks. One of the future research lines of the i4QPA would be the optimization of simulations to decrease the consumed time and computational power. The other future research line of the i4QPA is shared with the i4QLRT, that is, to communicate the i4QPA or/and i4QLRT to a system so that the results of the solutions affect the system and changes its configuration. The i4QLRT is focused on the industry, therefore, in the future it could be applied to different domains where control algorithms, operations or different learning models could be applied. And last but not least, the i4QLCP, in the future, should provide a basis for standardization, e.g. a new data quality auditing standard or the addition of data quality requirements to existing series of standards such as ISO 9000f.

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