Smart Process Qualification in Injection Moulding: An Industrial Case Study

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Abstract

Recent advancements in smart and continuous process qualification in injection moulding, crucial for industries like automotive manufacturing, have been significantly driven by the integration of Machine Learning, Edge Computing, and the Industrial Internet of Things. Hence, an industrial case study including the implementation and validation of the Data-Driven Continuous Process Qualification solution in Farplas, an automotive Tier-1 supplier describes significant advancements in this area. Leveraging Machine Learning and sensor data, the developed software package aims to improve defect detection over traditional visual inspections. Key Performance Indicators focused on moulding machine parameter optimisation and visual part inspection demonstrate the effectiveness of smart process qualification. The integration of the application, facilitated using Docker containers, marks a significant shift in Statistical Process Control, utilising AutoML for real-time analysis. The successful deployment in Farplas highlights enhanced manufacturing efficiency and quality, positioning Driven Continuous Process Qualification as a vital tool in industrial process optimisation.

This paper describes the conception, implementation and usage of AI solutions provided by European Project i4Q (Grant Agreement number: 958205 — H2020-NMBP-TR-IND-2018-2020 / H2020-NMBP-TR-IND-2020) to control and optimise the machining process.

Keywords

Industry 4.0, Plastic Injection Moulding, Artificial Intelligence, Predictive Process Control, Visual inspection

1. Introduction

The field of smart and continuous process qualification in injection moulding has seen significant advances in recent years, particularly in the context of quality control and process optimisation. This is crucial for industries like automotive manufacturing, where high-quality parts with complex geometries are essential. Such advancements are largely driven by the integration of Machine Learning, Edge Computing, and Industrial Internet of Things (IIoT) systems into the injection moulding process [1, 2]. The production process of injection moulding consists of melting and injecting polymers into a mould cavity under high pressure. Over time, it evolved to one of the most widely used processes in the automotive industry, as it allows the production of high-quality parts with complex geometries in a versatile and efficient way. However, it contains critical parameter monitoring, where scalability, repeatability, safety, and quality analysis of the parts is of great importance to ensure the performance of the final product and that it conforms to the standards.

Proceedings of the Workshop of I-ESA'24, April 10-12, 2024, Crete, Greece
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During the production process, the operators and process owners consistently and continuously undertake comprehensive quality control measures as part of their due diligence to analyse the quality of the various parts through various visual inspections. This approach allows for the potential detection of certain imperfections that might manifest on the surface of the parts under scrutiny, although it is important to note that other imperfections might prove to be more elusive and challenging to readily identify. To address and effectively mitigate this challenge, the Data-Driven Continuous Process Qualification solution (i4Q^{PQ}) has been developed, considering multiple factors and considerations. This comprehensive solution is intricately based on the application of advanced Machine Learning algorithms, which serve as the foundation for the systematic and expeditious detection of any potential defects that might be present within the parts. This detection process is facilitated through the utilisation and analysis of data that is diligently collected by the multitude of sensors that are strategically positioned within the production machines.

To demonstrate the possibilities and inherent capabilities of the Data-Driven Continuous Process Qualification, this article elucidates an industrial case study, which has been executed in the domain of the automotive Tier-1 supplier, namely Farplas. Furthermore, this work validates and enhances the underlying production process, to ensure efficiency and effectiveness.

2. About Farplas

Farplas is an automotive supplier part of Fark Holding that designs, develops and manufactures vehicle plastic systems such as interior/exterior parts, lighting systems, and electronic-based interior ceiling systems. Nowadays it has around 2,000 employees and 80 injection machines, on which approximately 10 different parts are produced with the design friendly and fastest production process, which is injection moulding. In these machines, the molten plastic material is injected into a mould cavity. Each produced part requires different cycle times, moulds, materials and sometimes different machines with individual parameters to achieve defect-free shifts.

2.1. Business Processes

The injection moulding process refers to filling the mould with the source material to produce parts with complex shapes. Farplas, as a plastic injection company, uses this process that has stages optimised for each part and mould. In the first step, heating, melting, and material homogenisation takes places. When the source material is ready, it is pushed into the mould to give shape. After ensuring that the material has properly been placed in the mould, it is allowed to cool within the mould to reach its final shape. Additionally, some produced parts may be sent as they are to customers in the automotive industry, and sometimes additional components assembly and paint operations are involved to create more sophisticated and aesthetic parts, resulting in a whole different product than what is produced solely through injection moulding.

Ensuring that produced parts align with standards and customer demands they are controlled and prepared for delivery. Material requisition and production schedules are generated monthly by supply chain professionals via SAP system.

Before sending the produced parts to the customers, the quality assurance process carried out, which ensures that the part meets the quality standards. Once the production of plastic parts has been completed, the operator or technician near the machine checks the parts through a visual inspection and by referencing to quality standards or negative models, which allows for comparison. This process allows the detection of surface imperfections such as dents, burrs, and scratches that may affect the aesthetics or functionality of the parts due to the variation of their characteristics. Then, imperfect parts are packaged, labelled, and documented in the system separately.

2.2. Analysis of KPIs

Although the injection moulding is one of the most used production processes in the automotive industry due to its repeatability, scalability, and consistency, the technique itself is complex and it is hard to detect defects on parts because of geometry, location, and visibility of defects can be changing during the process. Therefore, precise detection of defects is below the desired target. In a nutshell, with the help of rapid error identification, Farplas' main objective is to increase manufacturing process productivity and increase performance in the detection of defective parts.

To reach these goals and measure the effectiveness of the i4Q solutions, Farplas provides clear quantitative metrics, specific to the context of each implementation of solutions, called Key Performance Indicators (KPIs). The specification of these KPIs is defined under two business process, which are **Plastic Injection Moulding Machine Parameter Optimization** and **Plastic Injection Visual Part Inspection**. The former refers to the ability for predicting the appropriate features in order to produce certain vehicle parts and offering the necessary parameter adjustment, while the latter includes a visual inspection system, which will be implemented on the plastic injection moulding machine to check the parts where faults exist.

In the business process of **Plastic Injection Moulding Machine Parameter Optimization**, six KPIs are related to the effects of the i4Q solutions that will be tested on a demo machine in one of the Farplas factories. **KPI611 - Injection Cycle Time** refers to the average production time spent for each part, whose current value is 0.4631 and is expected to decrease by around 20% after the i4Q solutions development. **KPI612 - Unplanned Stop Time** refers to the time spent on manual optimising the injection process parameter per month, and it is expected to decrease by 20% reaching a value of 17,100 units of time. **KPI613 - Overall Equipment Effectiveness Index** (**OEE**), represents the availability of a work unit, and its current value is expected to be reduced by 5% to reach an 88%.

In addition to these KPIs, there are also **KPI614 - Quality Ratio** and **KPI615 - Availability**, which have a relationship between the Good Quantity (GQ) and the Produced Quantity (PQ), and a relationship between the Actual Product Time (APT) and the Planned Busy Time (PBT) for a work, respectively. Each one is expected to increase by 5%. The last one is **KPI616 - Effectiveness**, which shows the percentage ratio between the Actual Working Time (ATW) and Production Time (APT), which is expected to increase by 5% approximately.

In the second business process, **Plastic Injection Visual Part Inspection**, two main KPIs exist to critically measure the effectiveness of the i4Q solutions. One is **KPI621** - **Quality Control Time**, which refers to the monthly average time spent for manual quality control, the value of which is expected to be reduced by 5% until the target value of 5 seconds is reached. The last one is the **KPI622 - SAP Control Rate**, meaning accurately recording the parts into a digital SAP system would rise by 99% by the end of the i4Q Project.

3. Solutions Implementation and Algorithms

One of the i4Q solutions implemented in the Farplas infrastructure is the i4Q^{PQ}. This software is categorised as a microservice and provides essential services for process owners through the utilisation of sensor data derived from manufacturing machines. Its primary focus lies in the continuous evaluation of the Process Capability Index (Cpk). This evaluation involves the real-time reading of data streams and the subsequent presentation of said data over specified time intervals or product quantities. The outcome of this evaluation is then transformed into a non-normality performance index, which is a necessary adaptation in industrial applications where traditional Statistical Process Control (SPC) tools struggle to handle non-normal or complex distributions due to the presence of multi-sensor approaches and data-rich environments. The i4Q^{PQ} system also allows for the adjustment of individual parameters to facilitate personalised analysis.

Another key feature offered by i4Q^{PQ} is the ability to indicate distribution characteristics. By providing a distribution plot and highlighting confidence intervals for a selected number of recent products, the software effectively informs the process owner about the distribution over a specified time range or product quantity. Furthermore, i4Q^{PQ} facilitates capacity forecasting and forecast accuracy. It accomplishes this by predicting the process capacity for future time intervals based on the current conditions of the machine. This prediction is achieved through the utilisation of Automated Machine Learning (AutoML) techniques, which have gained increasing relevance in real-time streaming applications within the Internet of Things (IoT) and microservices architectures. Regarding the forecast of the Cpk-value, the machine learning library “Fedot” for the programming language Python is used. This AutoML library creates individualised Machine Learning pipelines for univariate forecasting. Since i4Q^{PQ} is concerning quality measurements over time, Fedot is highly suitable since it is applying Machine Learning models, also called autoregression. This methodology leverages the growing number of sensors integrated into manufacturing hardware and combines them with advanced statistical and Machine Learning methods, by weighting the most recent observations individually by their correlation to the preceding data point (**Figure 1**).

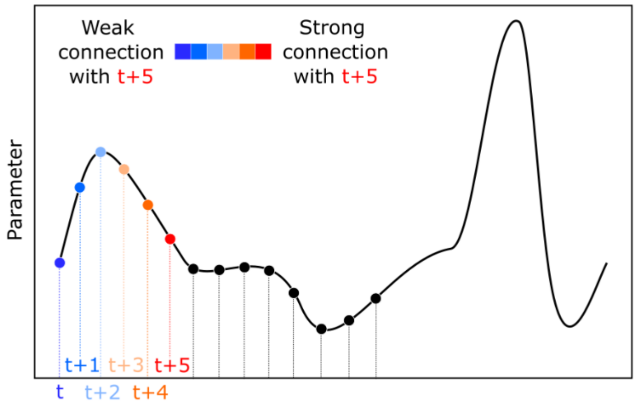

Figure 1. Parameter and time dependency

The capabilities of the i4Q^{PQ} solution extend to a Guided User Interface (GUI), which ensures the correct application and interpretation of its features (**Figure 2**). This interface is designed to support multiple languages, thereby broadening the applicability of the software. In terms of decision support, i4Q^{PQ} integrates an automated SPC system that reads critical limits inputted by the user and calculates the Cpk-value. This functionality is critical for process owners. Additionally, for a comprehensive understanding of process capabilities and future trends, i4Q^{PQ} combines real-time quality measurements with forecast values. This integration is particularly essential for industries that rely on real-time data processing and event-driven control.

In addition, i4Q^{PQ} possesses the capability to connect with real-time interfaces and conduct analyses based on varying environments, including both static and dynamic data environments. The deployment of i4Q^{PQ} is facilitated using open-source virtualisation software, which allows for easy integration into different operational environments. This enhances the software’s flexibility and operational efficiency.

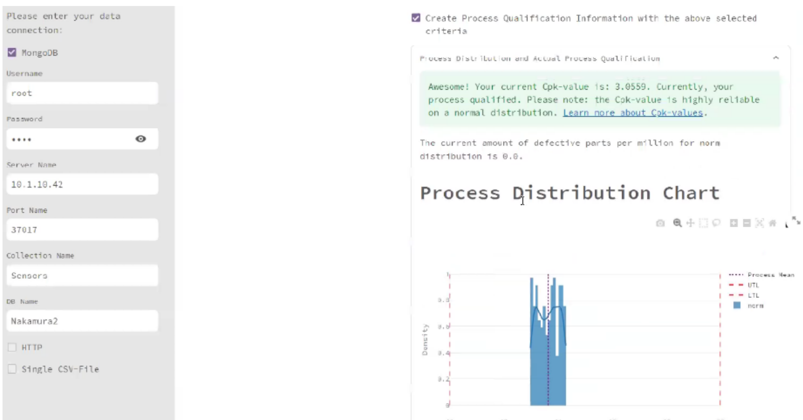

Figure 2. Part of the GUI of i4Q Process Qualification

4. Solutions Integration

The i4Q Project defined from the very beginning the technologies to be used during its course, with Docker containers being the standard way to develop and, later, deploy the different i4Q solutions. During the first months, the developers of these solutions focused on implementing the basic functionalities to meet the requirements established by the industrial partners (also known as i4Q Pilots).

After several months of development, the first demos of the i4Q solutions were presented and the deployment phase began. For this, Farplas prepared a machine on its premises and a remote connection mechanism to it so that the solution providers could connect and deploy the corresponding solutions there.

When the deployment of the i4Q solutions was finished, the integration phase began. This phase consisted of testing the quality of the different i4Q solutions, as well as analysing their fit with the requirements established with the help of solution providers and the Farplas company. This has helped to detect some problems and to make some adjustments to solve these undesired behaviours. With the introduction of these improvements, the integration phase has been successfully completed, with the solutions being integrated into the Farplas infrastructure as shown below (**Figure 3**).

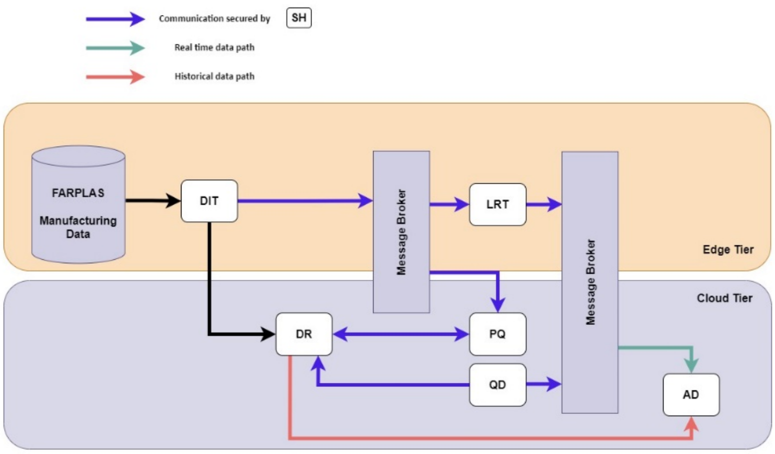

Figure 3. i4Q solutions Integration Diagram in Farplas infrastructure

Once the integration of the i4Q solutions in the Farplas pilot has been completed, as shown in Figure 3, the following solutions will be used: i4Q^{DIT}, i4Q^{DR}, i4Q^{LRT}, i4Q^{PQ}, i4Q^{QD}, i4Q^{AD} and Message Broker.

In order to achieve a satisfactory integration of all these, three different types of interactions between the i4Q solutions have been defined: (i) **direct interaction** – when one solution sends data to another directly (an example of this type is the interaction between the i4Q^{PQ} and i4Q^{DR} solutions, where the former produces a set of data and uses the latter to store it in a database); (ii) **secured direct interaction** – in this case, the interaction between the solutions is done directly and the use of SSL certificates is added to secure the communications (an example of this is the interaction between the i4Q^{QD} and i4Q^{DR} solutions, however, the other solutions connected by purple arrows in the diagram also use SSL certificates); (iii) **indirect interaction** – this type of interaction occurs when one solution uses a communication mechanism to send/receive data to/from another data source (an example of this is the i4Q^{DIT} solution, which obtains data from Farplas machines by subscribing to certain topics from the Kafka broker that the company has installed on its premises and then sends the processed data via the Message Broker so that other solutions, such as the i4Q^{LRT} solution, can consume it in real time).

5. Results

A key achievement is the transformation of SPC application in manufacturing processes, which is crucial for moulding injection machines where precision and consistent monitoring are essential. This transformation is facilitated by the integration of AutoML technologies and real-time monitoring in the i4Q^{PQ} solution. In this way, the implicit process knowledge of quality engineers is enhanced. Such an integration of statistical methods and ML algorithms has been shown to significantly improve control measurement systems in manufacturing, as demonstrated in the production of G8680x connectors in the automotive industry, where 100% control is performed immediately after the "injection moulding" process. [3] The novel process qualification of the i4Q^{PQ} solution caters to specific company domains and stands as an enabler for the application and continuous monitoring of the software. This aligns with studies on process variability in injection moulding, which emphasises the importance of SPC in monitoring and controlling process variability to prevent defects, low productivity, and poor-quality products. [4]

The integration of i4Q^{PQ} into the injection moulding operations of Farplas promises significant advancements in KPIs. For **KPI611**, enhanced process efficiency is achievable, indicating a more streamlined production with less waste of time and resources. **Unplanned Stop Time**, denoted as **KPI612**, can be reduced through i4Q^{PQ}'s automated parameter optimisation. This indicates fewer interruptions and a smoother operational flow.

Moreover, **Overall Equipment Effectiveness** (**KPI613**) stands to gain from a deeper process understanding. This comprehensive metric, indicative of the plant's productivity, is expected to improve as the system provides more detailed insights into the functioning of the equipment. **Quality Ratio** and **Availability** (**KPI614** and **KPI615**) are expected to see improvements facilitated by i4Q^{PQ}'s capacity for real-time monitoring and SPC applications. This will likely lead to a more consistent output of high-quality products and better uptime figures. Lastly, for **KPI616**, which assesses **Effectiveness**, the ability to better interpret products and parameters points to a more informed decision-making process, enabling fine-tuning of operations for optimal performance.

6. Conclusion

Applying i4Q^{PQ} in Farplas especially for moulding injection machines has demonstrated significant improvements. The software's adaptability, advanced forecasting SPC applications, AutoML technologies, and real-time monitoring capabilities position it as a valuable tool in enhancing the efficiency and quality of manufacturing processes. This paper has elucidated the substantial enhancements in manufacturing precision and control achieved through the application of AutoML and i4Q^{PQ} in injection moulding machine operations. i4Q^{PQ}'s integration of sophisticated statistical and Machine Learning algorithms has been demonstrated to significantly refine production control processes, optimising both efficiency and quality. Moreover, the qualification of i4Q^{PQ} underscores its value, promoting an alignment with SPC methodologies. In practical application, as observed with Farplas' utilisation of i4Q^{PQ}, these technologies have proven to markedly improve manufacturing outcomes. These advances not only fortify the competitive edge of manufacturing plants but also pave the way for a new standard in the industry, where continuous process control is synonymous with operational excellence and superior product quality.

Declaration on Generative AI

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

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