Received: 5 November 2024 | Revised: 10 March 2025 | Accepted: 24 March 2025 | Published online: 17 April 2025

RESEARCH ARTICLE

Journal of Data Science and Intelligent Systems
2025, Vol. 00(00) 1–11
DOI: 10.47852/bonviewJDSIS52024730

BON VIEW PUBLISHING

Quality Control and Process Optimization of Injection Molding using a Data-Oriented Approach in an Industrial Setting

Oumayma Haberchad[1,*] and Yassine Salih-Alj[2]

[1]*Control and Instrumentation Engineering Department, King Fahd University of Petroleum & Minerals, Saudi Arabia*

[2]*School of Science and Engineering, Al Akhawayn University in Ifrane, Morocco*

Abstract: This article proposes a data-driven scheme for quality control and process optimization of injection molding in industrial plants. The suggested approach enables the operators to find optimal process parameters that enable producing high quality parts. Additionally, it allows early detection of defects through monitoring variations of process parameters. The implementation of the suggested scheme is investigated in a factory, where an on-site test is conducted, and outcomes are validated using a process capability analysis. The adopted approach and various levels of data processing are described, followed by a detailed explanation of the implementation steps and an on-site test to assess its effectiveness. The obtained results indicate an increase in production quality, reduced surface-level defects by 52.47%, a 92.5% decrease in the variation of pressure, and less than 2 ms variation in injection time. Furthermore, the process capability analysis resulted in a stabilized process with lower weight variations as reflected with the related (cpk) index, proving the approach to be capable of producing conforming products.

Keywords: injection molding, process monitoring, quality control, data analysis

1. Introduction

Injection molding is one of the most popular processes in plastic manufacturing [1]. It accounts for 30% of all plastic production, and its global market size is expected to rise annually by 4.8% to reach 397.6 billion US dollars by 2030 [2]. Such an outcome is anticipated, since injection molding allows the production of complex parts in a short production time and at a low cost [3]. Despite its benefits, injection molding is a major generator of waist as defects are still a persisting problem. To address this concern, different methods were investigated. These methods focused on controlling the process and improving the quality of production [4].

Process control and monitoring are important procedures in injection molding. They entail monitoring the interaction between machine operation and the state of the resin. Ignoring a machine alarm or a control procedure can lead to huge losses since one injection cycle takes few seconds and can produce more than one part [5]. Nonetheless, process control has its set of challenges [6]. This is due to the different factors affecting operation, the nonlinear relationship between process parameters, and the large time delay in process variables [7]. Conventional methods relied heavily on operator's expertise and on trial-and-error methods [8]. However, the result was an inconsistency in the quality of production. Statistical methods were investigated, such as the Taguchi method and fuzzy logic [9]. These techniques were highly efficient in optimizing process parameters because of their ability to detect abnormal variations, but less efficient in dynamic control given their non-iterative nature [10].

Quality control is as important as process monitoring. Injected products go through multiple control units to ensure that no defective part is delivered to the customer. This makes quality control cost and time-consuming, since the process is mainly manual, and it comes at a later stage of the injection process [11]. Thus, relating variations of parameters to the quality of products becomes more challenging. Recent work has explored the use of cameras to inspect the quality of parts right after ejection [12]. However, visual appearance takes time to stabilize which may require additional inspections.

Considering a data analysis technique appeared to be an efficient solution. It promises better monitoring of the process and an overall improvement of the production quality [13]. For instance, different research work in literature focused on finding the process parameters that have the highest effect on production [14, 15]. However, the results differ from one finding to another given the high variability of process parameters.

New approaches relied on computer simulations such as Computer-Aided Engineering (CAE), cyber-physical production systems, and digital twins [16]. These technologies would allow modeling of the process, replication of injection conditions, and generation of large simulation-based datasets. Although the theoretical results showed high accuracy, applying the findings in real settings proves these methods to be less performing [17].

On the other hand, other research used machine learning (ML) techniques to predict the appearance of defects as well as the quality of injected products [18, 19]. Prominent results were found for defects related to dimensionality and weight with an accuracy

*Corresponding author: Oumayma Haberchad, Control and Instrumentation Engineering Department, King Fahd University of Petroleum & Minerals, Saudi Arabia. Email: g202423940@kfupm.edu.sa

higher than 90% [20]. However, results were less promising for surface-level defects since visual quality is far more challenging to describe and quantify [21]. Additionally, using such techniques requires huge amounts of data [22]. The latter can be hard to acquire, as many companies are not yet adopting digitalization in their factory floors. Subsequently, in many cases, records of defects are done manually, and they don't match the data generated by injection machines.

Since the robustness of an injection monitoring system is related to the ability to get reliable and time-based measurement of important states in the process [23] and given the efficiency and versatility of data-oriented techniques [13], this paper examines the viability of integrating a data-driven quality control and process optimization approach to overcome surface-level defects in a real injection molding unit. The primary objective of this study is to align process parameter variations with the quality of the ejected part. This is done by investigating the process parameters affecting the quality the most and finding process windows with low variations in these parameters, hence ensuring the reproducibility and consistency of good quality parts, while preventing surface-level defects.

The suggested approach provides the operator with an iterative framework that takes into consideration the dynamic nature of injection conditions and the high variations of process parameters. Additionally, this study provides a practical approach for dealing with surface-level defects. Indeed, successful implementation of the approach promises reducing the reliance on the multiple quality control procedure and paving the way for a fully automated process and quality control. This will ensure fast integration into the Industry 4.0 manufacturing scene, at a low cost and with eliminated defects.

The remainder of this paper is structured as follows. Section 2 presents the theoretical model of quality control and process optimization. Section 3 describes the implementation procedure of the suggested data-driven suggested scheme. Section 4 details the on-site industrial testing results along with the capability analysis. Finally, Section 5 concludes the paper.

2. Literature Review

2.1. Theoretical framework

In this section, the quality control and process optimization scheme will be described. As shown in Figure 1, the approach is divided into six levels: Data acquisition, data analysis, extraction of optimal parameters, process monitoring, quality control, and database.

2.1.1. Data acquisition

There are two data sets that need to be collected: process parameters and defect records.

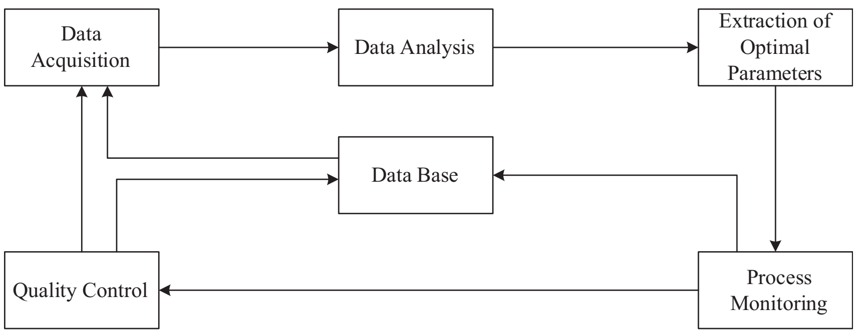
Process parameters are collected from injection machines. These machines are equipped with sensors that measure temperatures, pressures, and other parameters [24]. The data sets are in the form of time series. Each record corresponds to one injection cycle. Additionally, in a cycle, one or multiple parts can be produced. Data generated is extracted from the machine in different formats including: (.txt, .tqc, .csv).

Defect records, on the other hand, are collected manually. First, when the parts are ejected through visual inspections and at the end of the injection process once the shape and visual appearance of the part have stabilized to measure the weight and the dimensions of the part. As mentioned in Section 1, these operations make quality inspections cost-intensive, time-consuming, and sometimes prone to human error. Different techniques in the literature have explored methods allowing the automation of the process including [25] in which operators responsible for weight and shape inspections are replaced with auxiliary robots – which make the process aligned with Industry 4.0 manufacturing. Additionally, machine vision and deep neural networks have also been used for defect detection [26, 27]. Indeed, machine vision has the ability to cover the whole electromagnetic spectrum, while deep learning provides different techniques for defect detection such as defect detection context, learning techniques, defect localization, and classification which surpass the limitations of artificial visual inspections and eliminate manual ones. Furthermore, new classes of ML algorithms have emerged including reinforcement learning [28] and Generative Adversarial Networks (GANs) [29]. Using the game concept, GANs train a generator and a discriminator to inspect defects. These ensure the powerful feature pertainig to their generation ability that enables the expansion of defect datasets – resulting in an enhanced data.

2.1.2. Data analysis

At this level, data gathered will be cleaned, explored, and analyzed to identify patterns in process parameters and relate them to the occurrence of defects. Data cleaning enables us to remove corrupt and incomplete records from data [30]. After cleaning the data set, process parameters are visualized and explored to understand the effect of each one on the other. Additionally, records of defects are merged with process parameters data to verify how variations in process parameters can be a direct cause of appearance of defects. The analysis is carried out in Python programming software, given its ease of use and the variety of libraries it provides (Pandas, NumPy, Matplotlib).

Figure 1
General block diagram of the quality control and process optimization scheme



2.1.3. Extraction of optimal parameters

After analyzing the different data sets and identifying the relationship between them, the optimal process parameters are determined. This can be accomplished by identifying the parameter that has the highest effect on the quality of ejected parts and identifying process windows for good quality products [18]. Depending on the availability of data, different methods can be used to identify the parameter affecting the quality the most. This includes analyzing correlation matrices or applying ML classification algorithms, such as support vector machine (SVM), random forest, and gradient-boosted trees (GBT) [31].

On the other hand, identifying process windows for good production means determining parameter values resulting in no defects. By doing so, the variations in process parameters would be minimized with a consistent quality of production and better control over the process.

2.1.4. Process monitoring

Optimal process parameters deduced are inserted in the injection machine for a new production. Tolerances are specified as well in order to eliminate high variations in parameters and to alert the operators when parameters are out of the range specified [32]. Once production starts, the process can be monitored real-time using a graphical display [13]. The latter will enable the operator to visualize the process parameters and detect any instabilities in the process.

Thanks to the advancements in deep learning, new methods have emerged allowing seamless monitoring of the process, less reliance on manual maneuver, and effective handling of available data. This includes systems merging off-production representation learning, in-production dynamic calibration, and online monitoring for anomaly detection and root cause identification [33].

2.1.5. Quality control

At this level, the quality of ejected parts will be controlled. As previously discussed, records of defects are collected during and after production. This implies that there are two control procedures employed to assess the quality of production. The first one is carried out periodically during production [14]. The second is performed after the completion of production. The purpose of this procedure is to ensure that no defective part was left from the first control and to validate the quality of products through different measurements such as weight, and dimensions.

2.1.6. Data base

Data collected from injection molding machines and from quality control checkups will be stored in a database linked to the company server. This will provide access to historical data that will be used to train ML models and to predict the occurrence of defects [34].

3. Research Methodology

3.1. Implementation procedure in a factory

In this section, the proposed data-driven scheme is employed in the injection unit of an Automotive Moroccan company. Figure 2 illustrates the procedure used to implement the proposed scheme on the factory floor. The procedure is divided into six consecutive steps. Implementation results are elaborated in the following sections.

3.1.1. Product selection

To implement the suggested scheme as a mode of operation for all injected products, we must assess its effectiveness on one product. To select the product, we used the Pareto principle, also known as the 80:20 rule. This principle asserts that 80% of process's outcomes derive from 20% of its causes [35]. If we apply this principle to our case, we deduce that 80% of defects collected occurred in 20% of injected products. Figure 3 illustrates the Pareto distribution diagram of 6245 defects collected from 65 injected products. As observed, the first product P183, which is an automotive interior part, had the highest number of defects comprising 59% of total defects recorded. Accordingly, the quality control and process optimization scheme will be realized in this product.

3.1.2. Defect selection

After selecting the study product, the same principle is applied for selecting the target defect. Figure 4 illustrates the Pareto distribution diagram of defects detected in the chosen product. We observe that the white spot, a surface-level defect, is the highest recorded defect for the selected product with a percentage of 90.3%. This means that white spots affect the quality the most. Subsequently, white spots will be the target of analysis.

3.1.3. Data manipulation

In this step, white spots are investigated following the proposed scheme. As previously mentioned, two data sets are needed. Process parameter data were collected from the injection molding machine in a .csv format. The raw data contained {6923 rows × 19 columns}. The number of rows refers to the number of cycles, where four parts are ejected per cycle, and the number of columns refers to

Figure 2
Block diagram detailing the implementation procedure in the factory

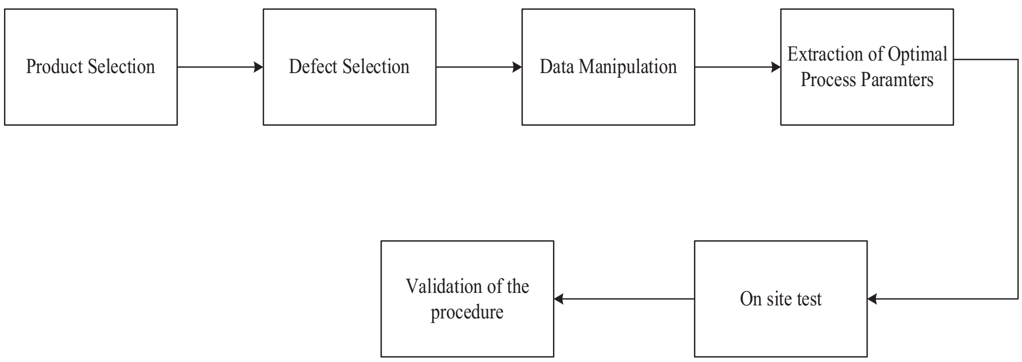


Figure 3
Pareto distribution diagram for product selection

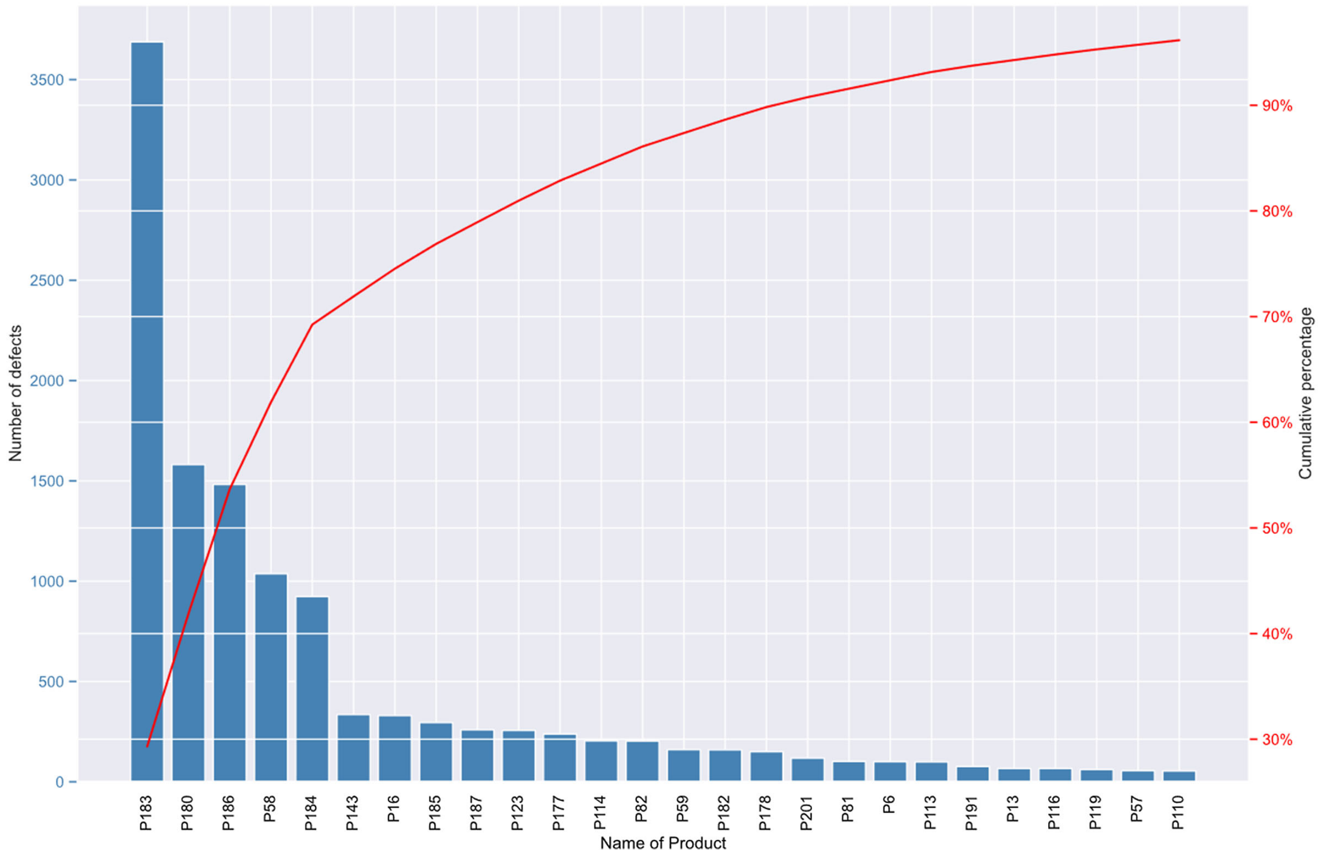
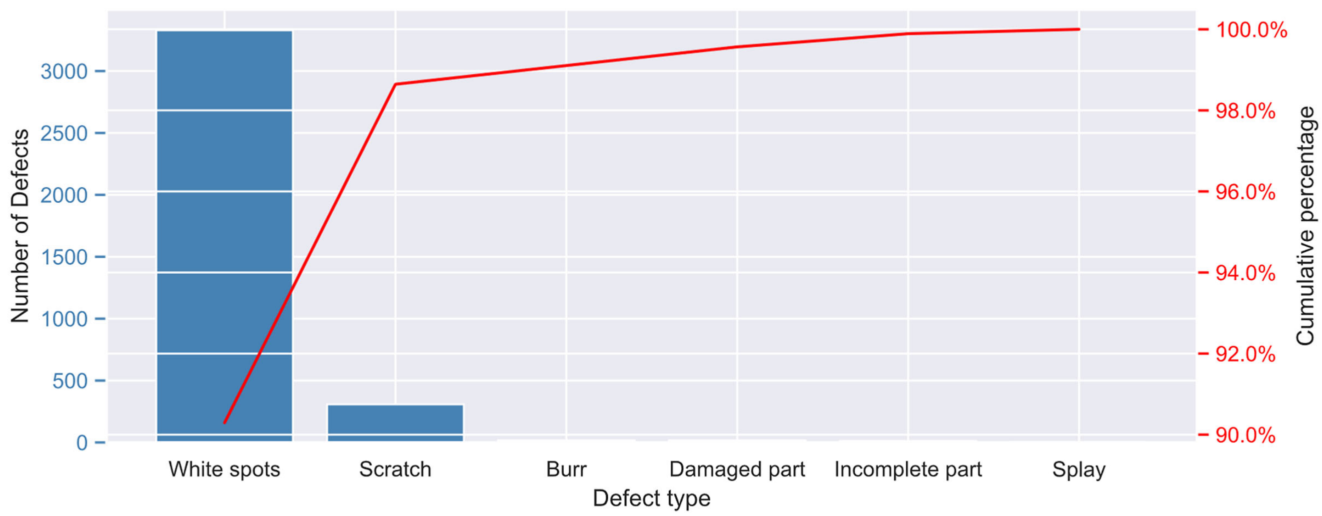


Figure 4
Pareto distribution diagram for defect selection



the process parameters being monitored. Defect data on the other hand was collected on an hourly basis for 11 shifts.

3.1.4. Data cleaning and exploration

Data extracted from the injection molding machine is manipulated using python programming software. We noticed that some rows or cells were empty. Table 1 presents the number of missing values found for each parameter. In injection molding, such records occur during downtimes of machines or when errors arise. An example of this is having long cycle times or having empty cells. Failure to remove these records will mislead the analysis. Therefore, cycles with missing or misleading process

Table 1
Number of missing values for every process parameter

Parameter	Number of missing values
Date	2
Time (s)	2
Cycles	2
Cycle time (s)	0
Injection time (s)	1
Dosing time (s)	0
Cushion (mm)	1
Max inj. p. (bar) (maximum injection pressure)	1
End of screw p. (mm) (end of screw position)	0
CY3 Temp (°C) (temperature in the third zone of screw)	0
mold cls time (s) (Mold closing time)	0
mold op time (s) (Mold opening time)	0
ps mld op (mm) (Position of the mold when open)	7
pos scr end ds time (mm) (Position of the screw at the end of dosing time)	0
PC pos (mm) (Position of PC)	0
Oil Temp (°C) (Oil Temperature)	0
ZR Temp (°C) (Temperature of the ZR)	0
Nozzle Temp (°C) (Temperature of the Nozzle)	0
CY1 Temp (°C) (Temperature of the 1st zone of cylinder)	0

parameter values were removed, and the shape of the dataset becomes {6914 rows × 19 columns}.

After that, a correlation matrix is plotted in Figure 5 to understand how each parameter relates to the other. Pearson's correlation coefficient was used to measure the linear relationship between two parameters, with values close to 1 indicating high positive proportionality, values close to −1 indicating high negative proportionality, and values close to 0 indicating low proportionality. Lighter colors mean high positive proportionality, and darker colors indicate high negative proportionality. We notice that the maximum injection pressure has a high positive correlation with different parameters, among them injection time, cushion, and end of screw retreat. This suggests that the maximum injection pressure is the parameter that affects the process the most.

As for defects, data collected were imported for analysis. Figure 6 illustrates the distribution of the white spot defect in time. The total number of white spot defects found during the 11 shifts is 41, and the highest hourly record was 6 white spot defects (recorded at 2 PM).

To better understand how formation of defects can be caused by high variations of parameters, we plotted some process parameters at the time we had the highest number of defects.

In Figure 7, the variation of injection time with time is displayed. We notice that the variations are between 0.6540 s and 0.6520 s. However, between 2:40:00 PM and 3:00:00 PM injection time decreased to 0.6510 s. In Figure 8, the dosing time is plotted. We observe that it increased until it surpassed the value of 2.85 s. In Figure 9, the maximum injection pressure is plotted.

Figure 5
Correlation matrix of the process parameters

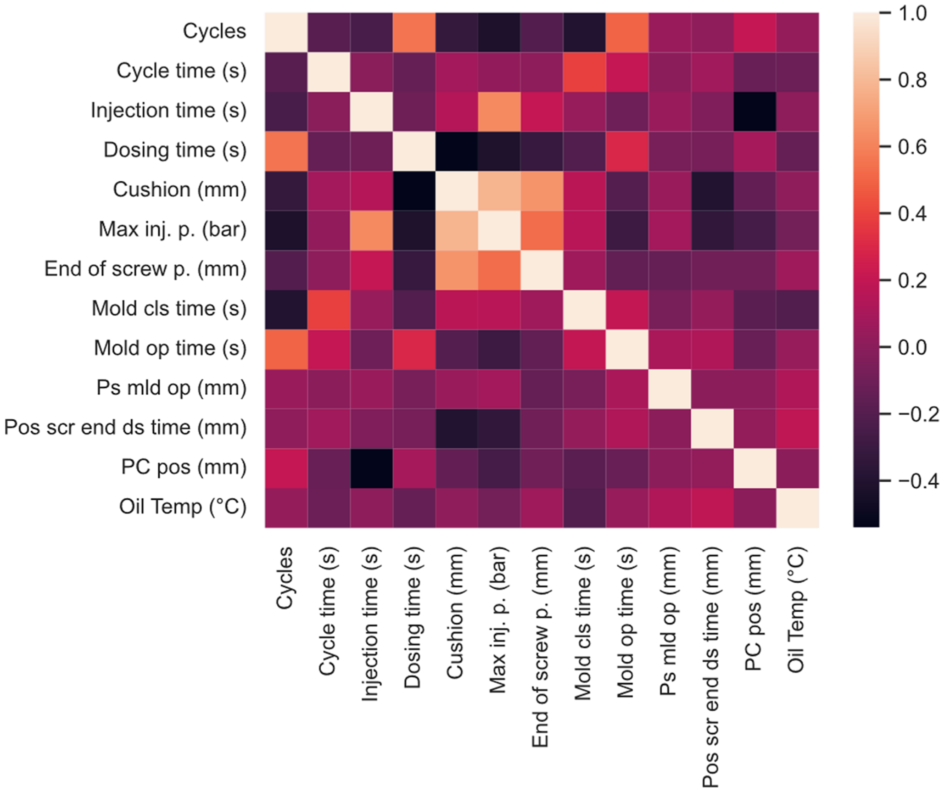


Figure 6
Distribution of white spot defect versus time

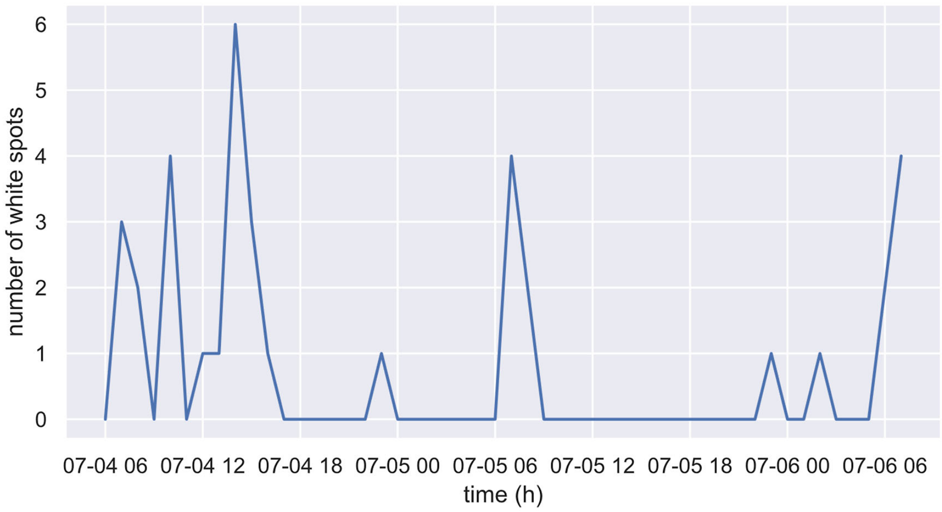


Figure 7
Graph of variations of injection time

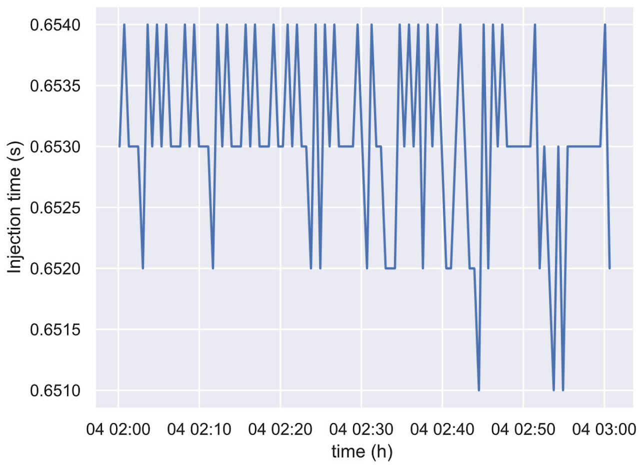


Figure 9
Graph of variations of maximum injection pressure

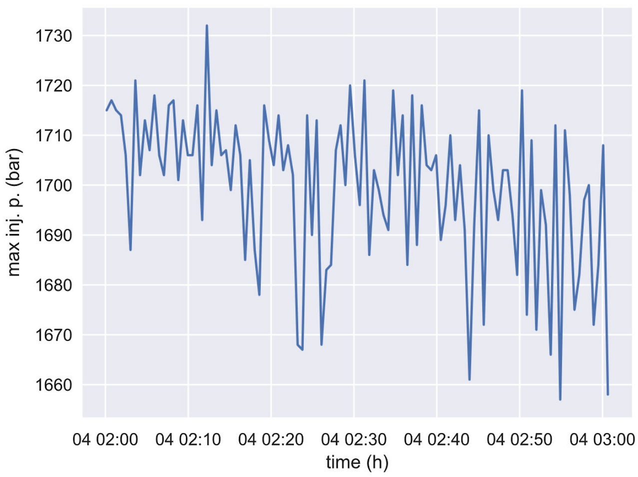
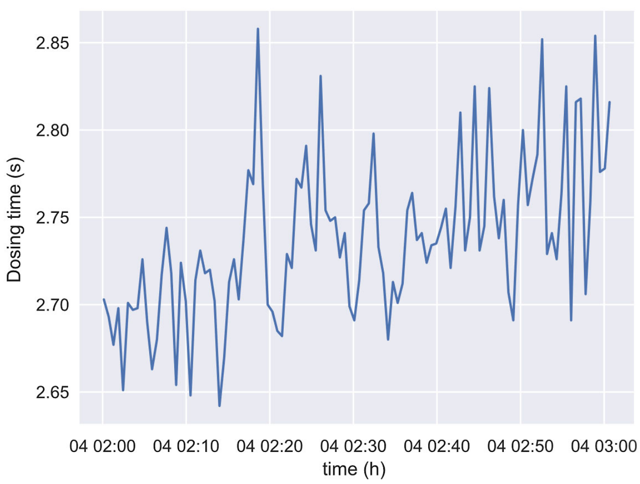


Figure 8
Graph of variations of dosing time



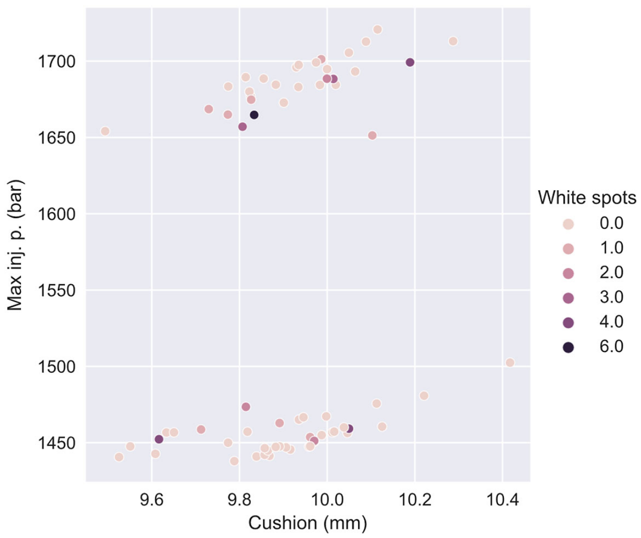
We notice that the pressure decreased to a value less than 1660 bar. This illustrates that the process is highly variable and in order to efficiently monitor it and to predict the occurrence of defects, these variations should be controlled.

After analyzing each data set separately, it is time to merge them. One restriction that was faced is that records of process parameters do not match the records of defects. This is because process parameters are recorded autonomously by the machine in each cycle, while records of defects were recorded on an hourly basis by operators on-site. To overcome this limitation, we increased the window of time for process parameters to match records of defects. The hourly record represents the mean values of process parameters for cycles produced in that hour. Subsequently, the number of defects recorded every hour is matched with the mean values of process parameters in that hour.

3.1.5. Extraction of optimal parameters

In this step, the optimal process parameters are extracted. These parameters reflect a stable process producing high quality parts. To

Figure 10
Distribution of white spots defect with respect to cushion and the maximum injection pressure



find these parameters, we need first to analyze the defect's distribution. Figure 10 is a scatter plot illustrating the distribution of white spots with respect to the maximum injection pressure and cushion area.

We observe that there are two clouds of points that are related to pressure variation. One cloud for values less than 1500 bar and the other is for values higher than 1650 bar. We also notice that a pressure lower than 1450 bar did not produce any defects.

Following this finding, we analyzed cycles for which the pressure was lower than 1450 bar. Table 2 details the statistical characteristics of the sample. We observe that the standard deviation is low as opposed to the whole sample, and the number of defects is 0. Using these results, mean values from the table are considered to be the optimal process parameters and the minimum and maximum values from the table represent the upper and lower tolerances.

Table 2
Statistical characteristics of the process parameters for cycles with a pressure less than 1450 bar

	Count	Mean	Std	Min	Max
Cycle Time (s)	16	35.32	0.3	35.05	36.12
Injection time (s)	16	1.18	0.01	1.17	1.19
Dosing time (s)	16	2.84	0.05	2.81	2.99
Cushion (mm)	16	9.82	0.14	9.53	9.96
Max inj. P. (bar)	16	1444.8	3.4	1437.92	1449.99
End of screw p. (mm)	16	50.49	0	50.49	50.49
CY3 Temp (°C)	16	240	0.02	240	240.06
White spots	16	0	0	0	0

4. Results and Discussion

4.1. On-site test results

To evaluate the reliability of the parameters deduced in controlling the process and reducing defects, an on-site trial was conducted: starting first by inserting the optimal parameters deduced in the injection molding machine followed by calibrating the velocity to obtain the desired pressure. Then, production is launched for four hours.

Table 3
Statistical characteristics of the test process parameters

	Count	Mean	Std	Min	Max
Cycle Time (s)	436.00	35.14	2.01	34.09	76.95
Injection time (s)	436.00	1.22	0.001	1.22	1.23
Dosing time (s)	436.00	2.81	0.05	2.62	3.05
Cushion (mm)	436.00	10.02	0.34	8.96	10.76
Max inj. P. (bar)	436.00	1443.35	8.75	1399.00	1473.00
End of screw p. (mm)	436.00	50.49	0.01	50.44	50.53
CY3 Temp (°C)	436.00	240.00	0.00	240.00	240.00
White spots	436.00	0.00	0.05	0.00	1.00

The test was monitored during production on an hourly basis and after production for quality control. Only one white spot defect was found, and it was during the hourly checkup.

Once the four hours had finished, test data were exported from the injection molding machine, and results were investigated. Table 3 describes the statistical characteristics of the test process parameters. Comparing the values obtained with values of Table 2, we notice that the mean values of test parameters are very close to the process optimization parameters. In addition, the variations are smaller, as observed in Figure 11. This indicates that test parameters are clustered tightly around the mean and that the test produced a homogenous sample with less variations. These results are well illustrated in Figure 12, where the points representing the products injected form one cloud, and the defect found had a pressure that exceeded the maximum tolerance.

4.2. Process capability analysis

To assess the efficiency of the proposed scheme, a process capability analysis was implemented. Process capability is a measure of the product uniformity of a process [36]. This analysis consists of statistical measurements used to evaluate the process's ability to produce parts meeting the required specifications and the extent of production homogeneity. Two indices are used, *cp* and *cpk*; they are formulated as:

$$Cp = \frac{USL - LSL}{6\sigma}, \tag{1}$$

$$Cpk = \frac{\min[(USL - mean), (mean - LSL)]}{3\sigma}, \tag{2}$$

where *USL* and *LSL* refer to the upper and lower specifications, and σ represents the standard deviation.

The *cp* index indicates if the process is within the specified range. The *cpk* index indicates if the process is centered between the lower and upper specification limits, where the *k* index is a scaled distance between the midpoint of the specification range and the process mean [37].

A process under statistical control requires a *cpk* value greater than 1. A stable process with a high *cpk* value is described as capable, meaning that it can yield conforming products. In the context of injection molding, capable processes are highly desirable. This is because they allow long-term repeatability of good parts while reducing operator intervention. This results in enhanced reliability and productivity. Additionally, a capable process can further optimize production by tightening the control limits and moving

Figure 11
Graph of injection time for test data

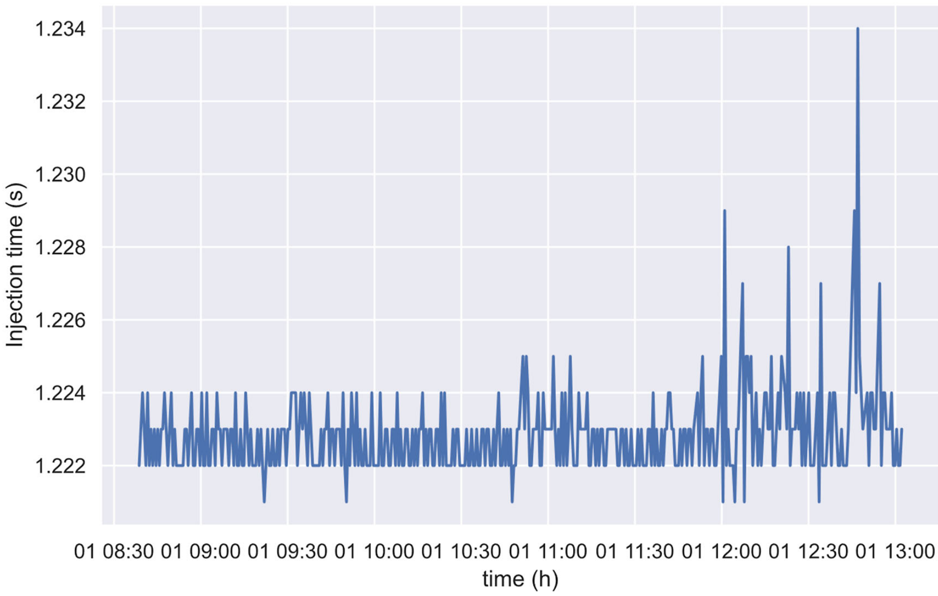
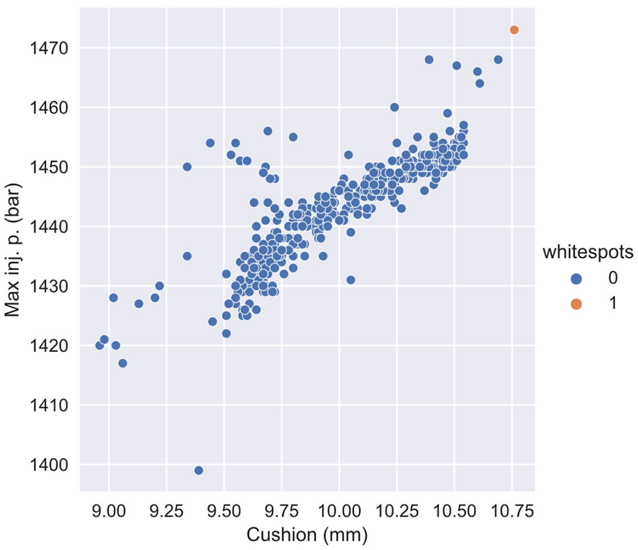


Figure 12
Distribution of injected parts with respect to cushion, maximum injection pressure, and number of white spots defects



towards lower specification limits that conserve energy and material which leads to increased profitability [36].

The process capability analysis was conducted for the part's weight given the ease of its measurement. This, indeed, is highly affected by the variations in process parameters. The analysis proceeded by measuring the weight of the selected product

Table 4
Process capability comparison between regular production and the on-site test

Cavities	Process type	*cp*	*cpk*	*Mean weight*
1	Production	18.94	16.17	23.17
	Test	26.08	23.66	23.10
2	Production	13.78	11.35	23.2
	Test	23.33	20.23	23.15
3	Production	19.25	19.15	23.2
	Test	2.06	1.98	22.96
4	Production	22.07	19.48	22.86
	Test	20.92	18.15	22.85

which was produced during the test and regular production. A total of 240 parts were weighed (30 parts per cavity). Then the *cp* and *cpk* indexes were calculated for each cavity. Table 4 details the obtained results. We notice that for all cavities, the values of the test's *cpk* index are greater than 1.33. In addition, for cavity 1 and 2, the values of test-related *cpk* are improved compared to those of regular production. To further illustrate these results, a control chart was plotted for cavities 1 and 2. As seen from Figures 13 and 14, parts produced from the test were consistent and had a lower variation in weight. This means that the deduced parameters from the data analysis scheme are more capable of producing a stable process. In addition to that, since the results differed from cavity to another, the study highlighted

Figure 13
Control chart comparison between normal production and test for cavity 1

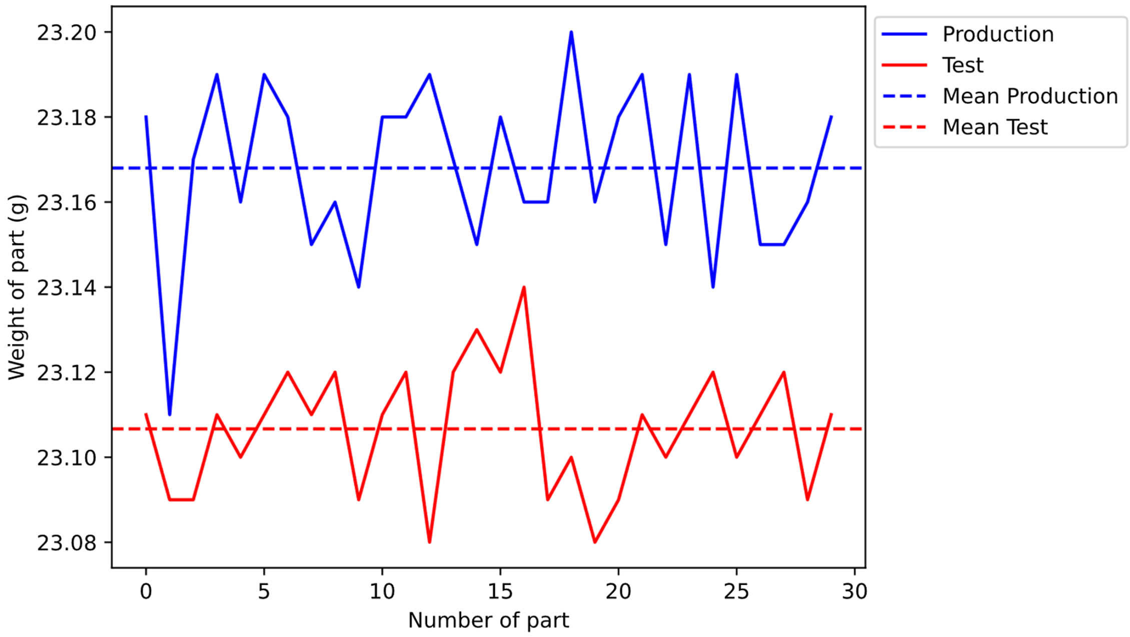
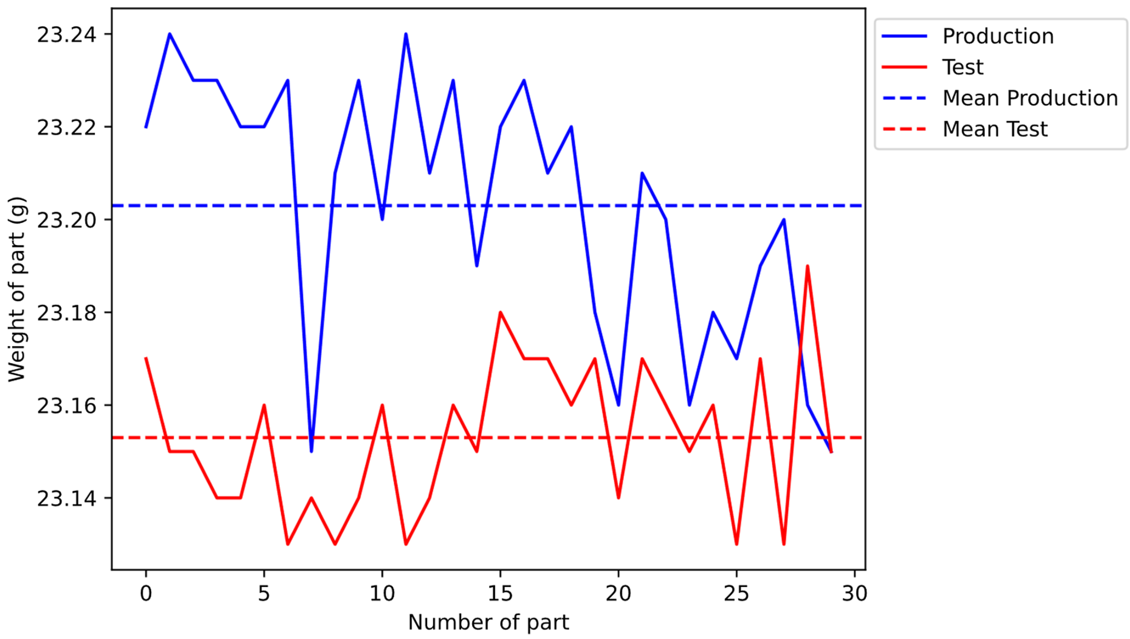


Figure 14
Control chart comparison between normal production and test for cavity 2



the importance of further exploration of the impact of in-mold process parameters [38].

5. Conclusion

In this paper, a data-driven approach for quality control and process optimization of injection molding was proposed.

A description of the approach and the different levels of data processing was provided, followed by an elaboration of the implementation steps in a factory, and an on-site test to evaluate its effectiveness. The main objective of the study was to examine the impact of process parameters on the visual quality of the end product through manipulation, control, monitoring, and optimization of these parameters and their variations. In addition to that, process stability was investigated to guarantee that optimized process parameters consistently deliver high quality parts, eliminate scrab, and allow efficient use of resources. The results obtained indicated that the pressure highly affects the product quality, as was observed in the correlation matrix, and the distribution of defects. Optimal parameters moved production to lower and tightened specification values. This resulted in low variations and better understanding of the effect of process parameters on the quality of the ejected parts. Test results showed that no defect was recorded when process parameters were within the specified range of optimal parameters. The capability analysis proved the scheme to be capable of delivering good quality parts thanks to the enhanced *cpk* index of cavity 1 and 2. The high values obtained in the capability analysis highlighted the opportunity for potential enhancement and optimization of specification limits.

The study can benefit from the use of more automated data acquisition methods for quality inspection to enrich the dataset and to synchronize data inspection with process parameters. This would allow complete and accurate monitoring of part quality. Furthermore, the availability of more data can allow the use of ML methods to deduce optimal process parameters. Additionally, the use of feedback control system can be explored to allow automated adjustment of the state of parameters, based on parts quality. Moreover, further investigation of in-mold parameters is needed to understand the difference in results obtained from one cavity to another.

Future work would address the limitation related to data availability by exploring methods to automate the process. Additionally, a comparison between machine and in-mold process parameters is to be conducted to evaluate the impact of each one on the end product.

Acknowledgement

We would like to thank the injection facility where the work was conducted.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Oumayma Haberchad: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Yassine Salih Alj:** Methodology, Validation, Writing – review & editing, Supervision, Project administration.

References

[1] Zhou, S., & Hrymak, A. N. (2024). Injection molding of polymers and polymer composites. *Polymers*, *16*(13), 1796. https://doi.org/10.3390/polym16131796

[2] *Injection Molding Market Size, Share & Trends Analysis Report by material (Plastics, metal, others), by application (Packaging, Consumables & Electronics, Automotive & Transportation), by region, and segment Forecasts, 2024–2030*. (n.d.). Grand View Research. Retrieved from: https://www.grandviewresearch.com/industry-analysis/injection-molding-market-report

[3] Farooque, R., Asjad, M., & Rizvi, S. J. A. (2021). A current state of art applied to injection moulding manufacturing process: A review. *Materials Today: Proceedings*, *43*, 441–446. https://doi.org/10.1016/j.matpr.2020.11.967

[4] Gim, J., & Turng, L. (2022). A review of current advancements in high surface quality injection molding: Measurement, influencing factors, prediction, and control. *Polymer Testing*, *115*, 107718. https://doi.org/10.1016/j.polymertesting.2022.107718

[5] Chang, K. (2015). Product cost estimating. In *Elsevier eBooks* (pp. 787–844). https://doi.org/10.1016/b978-0-12-382038-9.00015-6

[6] Xu, Y., Zhang, Q., Zhang, W., & Zhang, P. (2015). Optimization of injection molding process parameters to improve the mechanical performance of polymer product against impact. *The International Journal of Advanced Manufacturing Technology*, *76*(9–12), 2199–2208. https://doi.org/10.1007/s00170-014-6434-y

[7] Krauß, J., & Borchardt, I. (2023). Prediction and control of injection molded part weight using machine learning: A literature review. *Procedia CIRP*, *118*, 867–872. https://doi.org/10.1016/j.procir.2023.06.149

[8] Kutsbakh, A. A., Muranov, A. N., Semenov, A. B., & Semenov, B. I. (2019). Outstanding problems of numerical simulation of the process of injection molding of PIM-feedstocks and component quality. In *IOP Conference Series Materials Science and Engineering*, *525*(1), 012031. https://doi.org/10.1088/1757-899x/525/1/012031

[9] Chaves, M., Sánchez-González, L., Díez, E., Pérez, H., & Vizán, A. (2019). Experimental assessment of quality in injection parts using a fuzzy system with adaptive membership functions. *Neurocomputing*, *391*, 334–344. https://doi.org/10.1016/j.neucom.2019.06.108

[10] Zhou, X., Zhang, Y., Mao, T., & Zhou, H. (2017). Monitoring and dynamic control of quality stability for injection molding process. *Journal of Materials Processing Technology*, *249*, 358–366. https://doi.org/10.1016/j.jmatprotec.2017.05.038

[11] Ke, K., & Huang, M. (2021). Quality classification of injection-molded components by using quality indices, grading, and machine learning. *Polymers*, *13*(3), 353. https://doi.org/10.3390/polym13030353

[12] Zhang, Y., Shan, S., Frumosu, F. D., Calaon, M., Yang, W., Liu, Y., & Hansen, H. N. (2022). Automated vision-based inspection of mould and part quality in soft tooling injection moulding using imaging and deep learning. *CIRP Annals*, *71*(1), 429–432. https://doi.org/10.1016/j.cirp.2022.04.022

[13] Silva, B., Sousa, J., & Alenya, G. (2021). Data acquisition and monitoring system for legacy injection machines. In *2021 IEEE International Conference on Computational Intelligence and Virtual Environments for Measurement Systems and Applications*. https://doi.org/10.1109/civemsa52099.2021.9493675

[14] Silva, B., Sousa, J., & Alenya, G. (2021). Machine learning methods for quality prediction in thermoplastics injection molding. In *2021 International Conference on Electrical, Computer and Energy Technologies*. https://doi.org/10.1109/icecet52533.2021.9698455

[15] Cabrera, M. L., Zouhri, W., Zimmer-Chevret, S., & Dantan, J. (2024). An overview of strategies for identifying manufacturing process window through design of experiments and machine

learning techniques while considering the uncertainty associated with. *The International Journal of Advanced Manufacturing Technology*, *134*, 4981–5019. https://doi.org/10.1007/s00170-024-14480-0

[16] Nasiri, S., Khosravani, M. R., Reinicke, T., & Ovtcharova, J. (2024). Digital twin modeling for smart injection molding. *Journal of Manufacturing and Materials Processing*, *8*(3), 102. https://doi.org/10.3390/jmmp8030102

[17] Schmid, M., Altmann, D., & Steinbichler, G. (2021). A simulation-data-based machine learning model for predicting basic parameter settings of the plasticizing process in injection molding. *Polymers*, *13*(16), 2652. https://doi.org/10.3390/polym13162652

[18] Kumar, S., Park, H. S., & Lee, C. M. (2020). Data-driven smart control of injection molding process. *CIRP Journal of Manufacturing Science and Technology*, *31*, 439–449. https://doi.org/10.1016/j.cirpj.2020.07.006

[19] Kim, I., Na, J., Yun, J. P., & Lee, S. (2023). Deep feature selection framework for quality prediction in injection molding process. *IEEE Transactions on Industrial Informatics*, *20*(1), 503–512. https://doi.org/10.1109/tii.2023.3268421

[20] Polenta, A., Tomassini, S., Falcionelli, N., Contardo, P., Dragoni, A. F., & Sernani, P. (2022). A comparison of machine learning techniques for the quality classification of molded products. *Information*, *13*(6), 272. https://doi.org/10.3390/info13060272

[21] Goff, R. L. (2023). Visual quality prediction of plastic product based on thermographic images. *Materials Research Proceedings*, *28*, 1565–1574. https://doi.org/10.21741/9781644902479-169

[22] Jung, H., Jeon, J., Choi, D., & Park, J. (2021). Application of machine learning techniques in injection molding quality prediction: Implications on sustainable manufacturing industry. *Sustainability*, *13*(8), 4120. https://doi.org/10.3390/su13084120

[23] Hertz, R. A., Therkelsen, O., Kristiansen, S., Christensen, J. K., Hansson, F. A., & Schmidt, L. (2024). Development and validation of a 1D dynamic model of an injection moulding process and design of a model-based nozzle pressure controller. *Polymers*, *16*(10), 1432. https://doi.org/10.3390/polym16101432

[24] Ageyeva, T., Horváth, S., & Kovács, J. G. (2019). In-Mold sensors for injection molding: On the way to industry 4.0. *Sensors*, *19*(16), 3551. https://doi.org/10.3390/s19163551

[25] Zhou, Y., Hu, H., Ding, W., Gao, K., Li, D., & Gao, F. (2024). Cooperative distributed predictive control for smart injection molding systems with one-tap memory. *IEEE Transactions on Industrial Informatics*, *20*(6), 8850–8860. https://doi.org/10.1109/TII.2024.3378838

[26] Rotter, P., Klemiato, M., Knapik, D., Rosół, M., & Putynkowski, G. (2024). Inclusion detection in injection-molded parts with the use of edge masking. *Sensors*, *24*(22), 7150. https://doi.org/10.3390/s24227150

[27] Ren, Z., Fang, F., Yan, N., & Wu, Y. (2022). State of the art in defect detection based on machine vision. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *9*, 661–691. https://doi.org/10.1007/s40684-021-00343-6

[28] Párizs, R. D., & Török, D. (2024). An experimental study on the application of reinforcement learning in injection molding in the spirit of industry 4.0. *Applied Soft Computing*, *167*, 112236. https://doi.org/10.1016/j.asoc.2024.112236

[29] He, X., Chang, Z., Zhang, L., Xu, H., Chen, H., & Luo, Z. (2022). A survey of defect detection applications based on generative adversarial networks. *IEEE Access*, *10*, 113493–113512. https://doi.org/10.1109/access.2022.3217227

[30] Bhaskar, G. (2021). Data cleaning: Data preprocessing: Medium. *Medium*. Retrieved from: https://medium.com/data-preprocessing/data-cleaning-788b1cdd151f

[31] Polenta, A., Tomassini, S., Falcionelli, N., Contardo, P., Dragoni, A. F., & Sernani, P. (2022). A comparison of machine learning techniques for the quality classification of molded products. *Information*, *13*(6), 272. https://doi.org/10.3390/info13060272

[32] Calaon, M., Baruffi, F., Fantoni, G., Cirri, I., Santochi, M., Hansen, H. N., & Tosello, G. (2020). Functional analysis validation of micro and conventional injection molding machines performances based on process precision and accuracy for micro manufacturing. *Micromachines*, *11*(12), 1115. https://doi.org/10.3390/mi11121115

[33] Yan, P., Abdulkadir, A., Aguzzi, G., Schatte, G. A., Grewe, B. F., & Stadelmann, T. (2024). Automated process monitoring in injection molding via representation learning and setpoint regression. In *2024 11th IEEE Swiss Conference on Data Science,* 138–145. https://doi.org/10.1109/sds60720.2024.00027

[34] Gim, J., Yang, H., & Turng, L. (2023). Transfer learning of machine learning models for multi-objective process optimization of a transferred mold to ensure efficient and robust injection molding of high surface quality parts. *Journal of Manufacturing Processes*, *87*, 11–24. https://doi.org/10.1016/j.jmapro.2022.12.055

[35] Jana, P., & Tiwari, M. (2021). Lean terms in apparel manufacturing. In *Elsevier eBooks* (pp. 17–45). https://doi.org/10.1016/b978-0-12-819426-3.00010-2

[36] Rosato, D. V., Rosato, D. V., & Rosato, M. G. (2000). Injection molding handbook. In *Springer eBooks*. https://doi.org/10.1007/978-1-4615-4597-2

[37] *NIST/SEMATECH e-Handbook of Statistical Methods*. Accessed on Jan 14, 2025. Retrieved from: https://www.itl.nist.gov/div898/handbook/pmc/section1/pmc16.htm

[38] Haberchad, O., & Salih-Alj, Y. (2024). A cavity data acquisition system for defect prevention in injection molding. In *2024 10th International Conference on Applied System Innovation*, *29*, 244–246. https://doi.org/10.1109/icasi60819.2024.10547795

How to Cite: Haberchad, O., & Salih-Alj, Y. (2025). Quality Control and Process Optimization of Injection Molding using a Data-Oriented Approach in an Industrial Setting. *Journal of Data Science and Intelligent Systems*. https://doi.org/10.47852/bonviewJDSIS52024730