Integrating Machine Learning with Machine Parameters to Predict Plastic Part Quality in Injection Moulding

Manaf Al-Ahmad[1*], *Song Yang*[1], Yi Qin[1]

[1]Centre for Precision Manufacturing, Department of DMEM, The University of Strathclyde, Glasgow, United Kingdom

Abstract. The plastic injection moulding process is a critical manufacturing technique renowned for its high productivity, cost-effectiveness, and ability to produce intricate plastic components for various industries including medical and aerospace. The quality of the manufactured parts is influenced by several parameters, such as machine settings and mould characteristics, particularly thermal aspects. This paper specifically investigates the influence of primary machine parameters on part quality, excluding considerations of time, mould features, and cooling channel geometries. By focusing on the machine parameters and employing advanced machine learning methods, a comprehensive understanding is developed on how these factors can be utilised to predict the quality of the parts produced. The findings provide valuable insights into optimising the injection moulding process to enhance product quality and consistency.

1 Introduction

The quality of plastic parts is paramount in mass production, playing a critical role in industries such as medical equipment, aerospace, and micro and nano manufacturing. This importance has spurred extensive research into the plastic injection moulding process and the impact of various parameters on part quality. These parameters originate from both machine and mould characteristics, with cavity parameters intricately linked to machine settings. Consequently, this study focuses on machine parameters to determine their influence on part quality, employing Machine Learning (ML) techniques for quality prediction.

The following sections outline the stages of the injection process and highlight the key parameters involved. Certain parameters remain fixed after cavity and cooling channel design, emphasising the importance of monitoring modifiable parameters during the injection process for quality prediction. The impact of process parameters on quality criteria has been widely studied in manufacturing. For example, one study [1] examined the effects of nozzle temperature, screw rotational speed, mould temperature, and cooling time on energy consumption. Other research [2][3] examined the impact of melting temperature, injection pressure, packing pressure, and packing time, concluding that packing pressure is optimal for

* Corresponding autour : manaf.al-ahmad@strath.ac.uk

maximising tensile strength.Additionally, the Taguchi method has been employed to analyse the optimal parameters affecting part quality [4], including mould temperature [5]. Further studies [6] have focused on the effects of pressures at various stages of the process—such as injection pressure, holding pressure, and back pressure—on the final product quality. Moreover, Artificial Neural Networks and Support Vector Machines have been utilised to classify the quality of produced parts [7].

2 Experimental setup

The plastic parts were initially designed and simulated using SolidWorks Plastic software. This software facilitated virtual simulations to optimise parameters such as mould filling, cooling times, and material flow characteristics. SolidWorks Plastic was used to identify and theoretically implement optimal moulding conditions. These theoretical findings were then used to inform the physical experimental setup with targeted parameters for validation. The virtual 3D model was subject to the same conditions and environment as the physical model, with identical physical properties applied to the simulation model. Data from both models were then analysed. The design and simulation of the part, as shown in Fig1, were prepared using SolidWorks Plastic software. The material for this mould was ABS MAGNUM 3453 by Trinseo, with a melt temperature range of 230–270°C and a mould temperature range of 30–70°C, as presented in Table 1 as indicated in the software's material database.

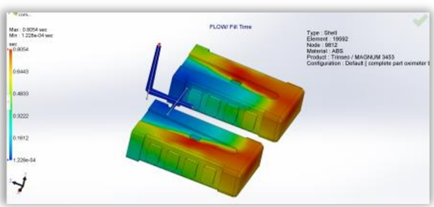

Fig. 1. The design and simulation of the part

Table 1. The results of simulations

Variables	Values
HP	24
SP	16
NT	20
HWT	20
Quality	0/1

The mould used consisted of two cavities, a cold runner, cooling channels, and a mould base. Its dimensions were 296 x 246 x 278 mm, with a cavity volume of 13.746 cm^3 and a runner volume of 0.66 cm^3. The two mould cavities were identical, so most quality and imbalance problems during the filling or packing phases were attributed to the cooling system.

A Battenfield 60T plastic injection moulding machine was utilised, equipped with a set of sensors for monitoring both machine and mould conditions. Key sensors installed on the machine included those measuring hydraulic pressure (HP), screw position (SP), nozzle temperature (NT), and heating water temperature (HWT). Concurrently, each mould cavity was outfitted with integrated pressure-temperature sensors to capture real-time data during production cycles. This dual-sensor approach aimed to provide comprehensive insights into both macroscopic machine operations and micro-level mould conditions influencing part quality. Sensor data were systematically collected using the Data Acquisition System (ComoNeo) developed by Kistler. This system facilitated precise monitoring and recording of process variables throughout the injection moulding process. Data were captured at high frequencies and stored in CSV format, ensuring compatibility with subsequent data analysis software. The injection moulding machine underwent rigorous calibration to ensure optimal performance and accuracy of sensor readings. The machine settings were standardised to maintain consistency across experimental trials, minimising variability and enhancing data reliability. During operation, the ComoNeo system continuously collected sensor data, including hydraulic pressures, screw positions, nozzle temperatures, and heating water temperatures from the machine, as well as pressure and temperature readings from each mould cavity. These data streams were synchronised and recorded in real-time, allowing for a comprehensive analysis of process dynamics and correlations between machine settings and mould conditions.

3 Data and methodology

Three experimental trials were conducted on a plastic injection production line, each comprising 400 cycles. These trials involved varying parameters at various stages of machine operation to evaluate their effects on the quality of the produced parts. Data were collected using a DAQ system and saved as CSV files.

Initially, several outliers were identified, particularly during the initial stages of production when the temperatures of the barrel, nozzle, and mould were too low and needed time to increase. Another issue was observed when the heating water temperature was reduced from 93°C to 40°C to study its impact on the quality and production process. Scatter plots of Time versus Hydraulic Pressure (HP), Screw Position (SP), Nozzle Temperature (NT), and Heating Water Temperature (HWT) were created to detect and remove outliers and missing values from the dataset. Fig 2 presents the scatter plot of various machine parameters recorded over time. After removing the outliers and missing values, the data were prepared for training.

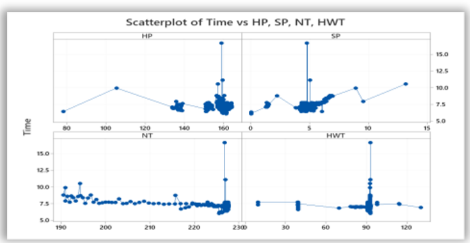

Fig. 3. Scatterplot of time vs HP, SP, NT, HWT.

A simple classification method was employed to predict the quality of the injection-moulded products. For this classification, the produced parts were labelled as good or bad, with each defective part marked as bad. Good parts were labelled as (0), and bad ones as (1).

The logistic regression model can be represented as:

$$log\left(\mathrm{P}\ (0)/\mathrm{P}\ (1)\right) = \beta 0+\beta 1\cdot \mathrm{HP}+\beta 2\cdot \mathrm{SP}+\beta 3\cdot \mathrm{NT}+\beta 4\cdot$$

Where:

- P (0) and P (1) are the probability of the good parts and bad parts, respectively.
- *β0* is the intercept.
- *β1, β2, β3, β4* are the coefficients for the independent variables HP, SP, NT, and HWT, respectively.

Using Minitab statistical software, the values of the intercept and coefficients were estimated for the logistic regression model, along with their standard errors and p-values. The analysis produced the following equation:

Y =190.8 + 0.1373 HP + 0.831 SP - 0.983 NT + 0.0630 HWT

The test results confirm that the logistic regression model, along with each factor (HP, SP, NT, HWT), significantly affects the quality of the produced parts, with the p-value of each factor being <0.05. This reinforces the importance of these factors in the manufacturing process and provides a solid basis for optimising these variables to improve product quality, The results also assessed the significance of the logistic regression model as a whole and the individual predictors included in the model, as presented in Table 2.

Table 2 Analysis of variance (ANOVA) for all factors.

Analysis of Variance

Source	DF	Wald Test Chi-Square	P-Value
Regression	4	27.02	0.000
HP	1	7.72	0.005
SP	1	9.12	0.003
NT	1	10.03	0.002
HWT	1	7.72	0.005

4 Data training

4.1 Machine learning (ML) Models

To train the data, it was split into three sets: 60% for training, 20% for validation, and 20% for testing. To ensure that all continuous factors are on the same scale, standardisation was applied to all factors, which can improve model performance. Four ML models were applied to the dataset: Logistic Regression, Random Forest, Support Vector Machine (SVM), and Gradient Boosting Classifier (GBC). The Table 3 present the results of the four ML models that applied in this study.

Table 3. The results of ML models.

Model	Accuracy	Precision (Class 0)	Precision (Class 1)	Recall (Class 0)	Recall (Class 1)	F1-Score (Class 0)	F1-Score (Class 1)	True Positives (TP)	True Negatives (TN)	False Positives (FP)	False Negatives (FN)
Logistic Regression	0.6812	0.69	0.67	0.69	0.67	0.69	0.67	45	48	26	19
Random Forest Classifier	**0.9710**	1.00	0.94	0.94	1.00	0.97	0.97	67	67	4	0
Support Vector Machine	0.6957	0.75	0.65	0.61	0.79	0.67	0.72	53	43	28	14
Gradient Boosting Classifier	**0.9855**	1.00	0.97	0.97	1.00	0.99	0.99	67	69	2	0

Random Forest: This model demonstrated high precision, recall, and F1 scores for both classes, indicating excellent performance in distinguishing between good and bad parts. The confusion matrix provided insight into specific classification errors, showing very few misclassifications (only 4 false positives and 0 false negatives).

Gradient Boosting Classifier: This model achieved an impressive accuracy of about 98.55%, correctly classifying all the test data. The confusion matrix showed very few misclassifications (only 2 false positives and 0 false negatives), indicating the model's exceptional reliability.

4.2 Receiver Operating Characteristic (ROC) curves

The ROC curve plots the True Positive Rate (TPR) against the False Positive Rate (FPR).
AUC for Training Data: 0.9824, indicating excellent performance on the training set.
AUC for Test Data: 0.9434, indicating particularly superior performance on the test set.
The model performs much better than random guessing. The high AUC values for both training and test datasets suggest that the model is highly effective at distinguishing between positive and negative classes. The slight drop in AUC from training to test set indicates some overfitting, but the model still generalises well to unseen data.
In Fig 4, the ROC curve in the left panel shows the model's performance in distinguishing between positive and negative classes, with an AUC of 0.9824 for the training set and 0.9434 for the test set, indicating excellent performance. The gain chart in the right panel illustrates the model's effectiveness in capturing true positives, with both the training and test sets showing high true positive rates, demonstrating the model's reliability and predictive power.

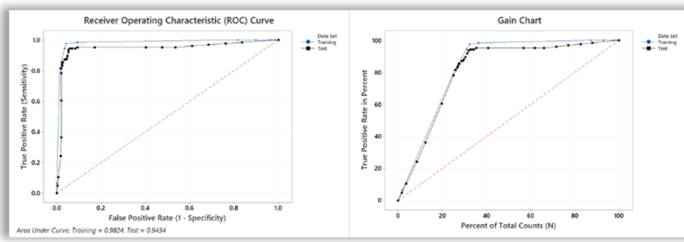

Fig.4. Area Under the Curve (AUC):

4.3 Model improving

To improve the selected ML model, enhancements in hyperparameter tuning and cross-validation were applied. Hyperparameter Tuning: This process identifies the best combination of hyperparameters for a model. Cross-Validation technique ensures that the model generalises well to unseen data by validating it on different subsets of the data. The Table 4 shows that both Random Forest and Gradient Boosting models were subjected to these improvements.

Table 4. hyperparameter tuning and cross-validation parameters for RF and GB

Model	Parameters	Best Cross-Validation Score	Precision (Class 0)	Recall (Class 0)	F1-Score (Class 0)	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)	Accuracy	Confusion Matrix
Random Forest	bootstrap: False, max_depth: None, min_samples_leaf: 2, min_samples_split: 5, n_estimators: 100	0.9514	0.96	0.97	0.96	0.94	0.91	0.92	0.95	[[64, 2], [3, 29]]
Gradient Boosting	learning_rate: 0.2, max_depth: 4, min_samples_leaf: 4, min_samples_split: 2, n_estimators: 50, subsample: 0.8	0.9539	0.95	0.91	0.93	0.83	0.91	0.87	0.91	[[60, 6], [3, 29]]

The results indicated that Gradient Boosting slightly outperformed Random Forest in terms of accuracy and F1-score for Class 1, but Random Forest showed a better balance across all metrics.

5 Conclusions

This study demonstrates the significant impact of machine parameters on the quality of plastic injection moulded parts. Using Machine Learning (ML) techniques, including logistic regression, Random Forest, SVM, and Gradient Boosting Classifier (GBC), The part quality was predicted effectively. Data from a calibrated injection moulding machine confirmed that hydraulic pressure (HP), screw position (SP), nozzle temperature (NT), and heating water temperature (HWT) are key factors. Among the ML models, Gradient Boosting Classifier achieved the highest accuracy at 98.55%, with both Gradient Boosting and Random Forest showing excellent performance and minimal misclassifications. ROC analysis validated the models' effectiveness, and hyperparameter tuning further refined their accuracy.
In conclusion, advanced ML techniques can significantly enhance the prediction and improvement of part quality in plastic injection moulding, providing a solid foundation for process optimization in various industries.

References

1. Meekers, I., Refalo, P. and Rochman, A., 2018. Analysis of process parameters affecting energy consumption in plastic injection moulding. Procedia CIRP, 69, pp.342-347.
2. Singh, G., Pradhan, M.K. and Verma, A., 2015. Effect of injection moulding process parameter on tensile strength using Taguchi method. International Journal of Industrial and Manufacturing Engineering, 9(10), pp.1844-1849.
3. Aminabadi, S.S., Tabatabai, P., Steiner, A., Gruber, D.P., Friesenbichler, W., Habersohn, C. and Berger-Weber, G., 2022. *Industry 4.0 in-line AI quality control of plastic injection molded parts. Polymers, 14(17), p.3551.*
4. Fei, N.C., Mehat, N.M. and Kamaruddin, S., 2013. Practical applications of Taguchi method for optimization of processing parameters for plastic injection moulding: a retrospective review. International Scholarly Research Notices, 2013(1), p.462174.
5. Mehat, N.M. and Kamaruddin, S., 2011. *Investigating the effects of injection molding parameters on the mechanical properties of recycled plastic parts using the Taguchi method. Materials and Manufacturing Processes, 26(2), pp.202-209.*
6. Amran, M., Salmah, S., Zaki, M., Izamshah, R., Hadzley, M., Sivarao, S., Kasim, M.S. and Amri, M., 2014. *The effect of pressure on warpage of dumbbell plastic part in injection moulding machine. Advanced Materials Research, 903, pp.61-66.*
7. Silva, B., Sousa, J. and Alenya, G., 2021, *December. Machine learning methods for quality prediction in thermoplastics injection molding. In 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET) (pp. 1-6). IEEE.*