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Uncertainty analysis on a Naïve Bayes prediction model for the plastic injection molding process

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Abstract

In plastic injection molding, efficient clamping force plays a critical role in maintaining product quality, minimizing energy consumption, and extending the lifespan of molds. Traditional methods often rely on empirical rules or fixed maximum force settings, which can lead to inefficiencies and higher costs. Therefore, a reliable prediction model can be a solution to optimize the injection molding process. Such a model has the ability to balance defect reduction, operational efficiency, and equipment durability. It also can correlate the complex interactions between process parameters and their associated uncertainties.

This study investigates the injection molding of plastic bushing (size 63 mm) as the case study. A Plackett-Burman Design of Experiments (DOE) with two levels for six key factors (melt temperature, cooling time, packing time, holding pressure, injection pressure, and injection time) is used as the screening step. This method offered 36 experiments and after the analysis, holding pressure showed almost no impact on the maximum clamping force, leading to its exclusion from further analysis. Then, a Central Composite Design (CCD) was employed for the remaining five factors, considering five levels for each, resulting in 32 experiments. Finally, a Naïve Bayes algorithm was trained to predict the results of the process, and its uncertainty was evaluated using the bootstrap sampling method. The findings of this study provide a clear understanding of developing high-quality prediction models with low uncertainty in prediction which can lead to optimizing the injection molding parameters.

Machine learning, Plastic injection molding, Uncertainty evaluation, Prediction models

1. Introduction

With a continuous increase in demand for plastic components, the need for higher-quality and cost-effective production is greater than ever. Emerging new technologies such as artificial intelligence (AI) have helped achieve this goal much more easily, as demonstrated in, e.g., [1]. Many studies have employed machine learning models to predict different quality attributes in the injection molding process such as warpage [2], shrinkage [3], weld lines [4], and blush [5]. Some other studies also tried to optimize multiple factors at the same time [6].

Even after implementing all these advanced prediction models, there is a lack of uncertainty analysis for the machine learning prediction models due to their black-box nature [7]. There are some grey-box or white-box machine learning prediction algorithms in the literature, including decision trees, logistic regression, random forest, Naïve Bayes, etc. Since these grey-box and white-box algorithms are interpretable (in contrary to the usual black-box algorithms), they provide mathematical prediction equations that are suitable for conducting uncertainty evaluations [8].

This study focuses on implementing uncertainty analysis on the Naïve Bayes algorithm to evaluate the clamping force of the injection molding process. The bootstrap technique was adopted by considering 100 resamplings to generate more prediction equations in order to evaluate the uncertainty of the coefficients in the equation [9].

2. Methods

To predict the Maximum Required Clamping Force in the injection molding process, a Placket-Burman DOE was employed as the screening step to evaluate the effectiveness of the six factors of melt temperature, cooling time, packing time, holding pressure, injection pressure, and injection time. After doing FEM simulations using Autodesk Moldflow and analyzing the results, it was revealed that all the factors except holding pressure affect the maximum clamping force. Then the analysis was continued with the significative factors using a CCD design of experiments which recommended 32 experiments to be executed. After the simulations, we employed a Naïve Bayes algorithm. It is a simple yet powerful machine learning model which is based on Bayes' Theorem based on the assumption that the predictors are independent of each other. Naïve Bayes (as a white-box algorithm) is known for being computationally efficient and interpretable. Unlike complex black-box models such as neural networks, Naïve Bayes derivates transparent predictions from straightforward probabilistic calculations.

This study aims at managing uncertainty in predictions. Naïve Bayes naturally provides corresponding probabilities, which indicate the model's confidence in its predictions. Our dataset consisted of 68 samples, which were used to train the Naïve Bayes model. The following equation is the result of the trained model:

G = (-1702,371) + (7.924)a + (-0.770)b + (-0.692)c + (0.226)d + (3.662)e + (-17.420)f

Here, *G* represents the Maximum Required Clamping Force, while the variables *a*, *b*, *c*, *d*, *e*, and *f* correspond to the melt temperature, cooling time, packing time, holding pressure, injection pressure, and injection time, respectively. See Table 1 for further details.

To better understand the uncertainty in the model's predictions, we applied bootstrap sampling. Bootstrap operates by generating multiple resampled datasets from the original data, which allows for investigating how model parameters vary across different iterations and how stable the results are. A series of 100 bootstrapped sample datasets were created, each containing 68 samples generated by resampling the original data with replacement. For each of these datasets, the Naïve Bayes model was retrained, producing 100 unique prediction equations.

2.1. Geometry and the material

The part under study is a plastic bushing with a size of 63 mm, used in the pipes and fitting industry. The mold has two cavities and the validation tests are conducted experimentally. A 2D and 3D view of the part can be observed in Fig.1 and Fig.2, respectively. The material used to manufacture the component and for the corresponding simulations was UPVC (Unplasticized Polyvinyl Chloride) Benvic IR705.

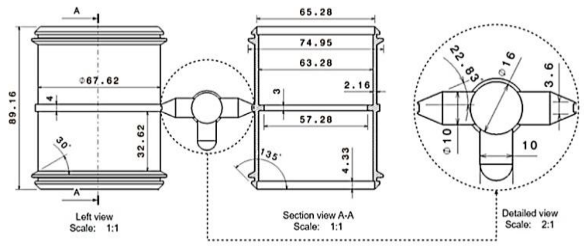

Figure 1. 2D view of the cavities and the runner system

Figure 2. 3D view of the bushing size 63 mm [5]

3. Results

Since each of the 100 generated models was trained on a slightly different dataset, the coefficients of the resulting equations varied slightly as well. This variability is key to evaluating the standard deviation of the coefficients and evaluating the uncertainty of the model. Table 1 represents the uncertainty of the variables and the coefficients of the mathematical model.

Based on Table 1, C_1, C_2, C_4, and C_5 are the most influential coefficients on the variance of the model, consequently influencing the expanded uncertainty. The expanded uncertainty for clamping force is 1.2E2 tonnes which compared to the 1.56E2 tonnes predicted by the equation, shows a 76.3% relative interval.

Table 1. Uncertainty evaluation of the mathematical model

Symbol	Value	$u_j^2(y)$ [t^2]
a [°C]	193.00	5.2E-4
b [s]	22.50	4.9E-6
c [s]	6.50	4.0E-6
d [MPa]	64.70	4.3E-7
e [MPa]	130.00	1.1E-4
f [s]	8.00	2.5E-3
C_0 [t]	-1702.37	4.8E-2
C_1 [t/°C]	7.92	1.3E3
C_2 [t/s]	-0.77	8.5E1
C_3 [t/s]	-0.69	5.8
C_4 [t/MPa]	0.23	1.4E2
C_5 [t/MPa]	3.66	2.1E3
C_6 [t/s]	-17.42	5.0
eps [t]	0.00	5.8E-2
G = Max clamping force [t]	1,56E2	
	Variance of G [t^2]	3.6E3
	Expanded uncertainty U(G) [t]	1.2E2
	Relative expanded uncertainty	76.3%

5. Conclusion

Based on the results, it is clear that applying the bootstrap sampling method can improve the model's robustness. By generating 100 bootstrapped samples of the initial model, the variability contribution of the coefficients and variables can be evaluated and compared. This leads to a better understanding of the reliability of the model.

The combined expanded uncertainty of the model includes all the uncertainties related to the coefficients and the variables. While the coefficients C_1, C_2, C_4, and C_5 show the highest influence on the uncertainty, the combined relative expanded uncertainty of the model is 76.3%. This relatively high level of uncertainty indicates that further optimization could be applied, and will be the objective in future work. As a solution to improve (i.e., to decrease) the uncertainty levels, the number of bootstrapped samples can be increased. We can go for 1000 and 10000 bootstrapped samples in future studies to test how sampling size can affect the uncertainty of the prediction model. Additionally, employing the method on a wider dataset might show further and improved capabilities of the method.

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