Data-Driven Identification of Remaining Useful Life for Plastic Injection Moulds

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Abstract. Throughout their useful life, plastic injection moulds operate in rapidly varying cyclic environments, and are prone to continual degradation. Quantifying the remaining useful life of moulds is a necessary step for minimizing unplanned downtime and part scrap, as well as scheduling preventive mould maintenance tasks such as cleaning and refurbishment. This paper presents a data-driven approach for identifying degradation progression and remaining useful life of moulds, using real-world production data. An industrial data set containing metrology measurements of a solidified plastic part, along with corresponding lifecycle data of 13 high production volume injection moulds, was analyzed. Multivariate Statistical Process Control techniques and *XGBoost* classification models were used for constructing data-driven models of mould degradation progression, and classifying mould state (early run-in, production, worn-out). Results show the *XGBoost* model developed using element metrology & relevant mould lifecycle data classifies worn-out moulds with an in-class accuracy of 88%. Lower in-class accuracy of 73% and 61% were achieved for the compared to mould-worn out less critical early run-in and production states respectively.

Keywords: Smart manufacturing · Injection moulding · Data-driven model · Machine learning · Predictive maintenance

1 Introduction

High-volume manufacturing processes such as plastic injection moulding, require considerable upfront investment in tooling to develop a reliable moulding operation [1]. Consequently, manufacturers are keen to maximize tool productivity by eliminating unplanned maintenance, minimizing part scrap, and extending the useful life of their injection moulds. Previous research has developed physics-based models of wear mechanisms affecting functionality of the mould

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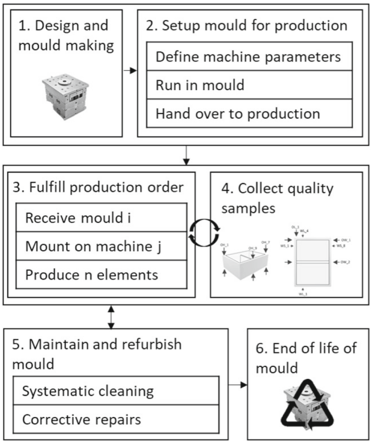
and the quality of the moulded element, and validated them using simulation and controlled experimental studies. Engelmann et al. [2] describe the progression of failure modes associated with specific components within a mould by optical inspection. Zabala et al. [3] develop a wear model quantifying the wear of the mould using a tribometer, erosion test, gravelometer and electro-chemical impedance spectroscopy with varying mould coatings and plastics raw material. Zhong et al. [4] compare the wear rate of three insert materials and determine the surface texture of the elements (using an electron microscope) as a function of injection cycles. However, these studies do not evaluate the applicability of the developed models to predict longevity of moulds in real-world production environments. To overcome these constraints, a variety of data-driven approaches and machine learning models have been proposed for estimating element quality (such as element weight, dimensions, etc.) as function of process and machine data. Schulze et al. [5] propose an automated workflow for developing predictive quality models for a plate specimen based on a variety of machine and process parameters. Ogorodnyk et al. [6] classify low and high quality elements on-line as a function of machine and process parameters. Frumosu et al. [7] present an industrial application to predict mould lifetime from a data set containing initial process settings and tool characteristics such as, layout, construction, and number of cavities. In spite of these studies, there is limited understanding on which models are applicable towards mould longevity prediction as the accuracy of such models are limited by the nature and resolution of data that can be effectively measured on the factory floor.

In this paper, we aim to address the above knowledge gap by systematically analyzing long-term mould life-cycle data collected from a real-world industrial case. Results from our study contribute to existing research on mould degradation prediction by, (i) presenting existing data-related and modeling-related challenges, and (ii) identifying opportunities for successful application of data-driven prediction models for injection mould degradation and classifying moulds based on remaining useful life.

2 Industrial Data Set

In this section, we introduce the typical life-cycle of an injection mould and relevant data collected at our industrial partner. Below we use the term "part" as reference to the physical components of a mould and "element" as reference to the solidified product from the moulding process. Our main goal is to use metrology samples that are commonly collected in industrial injection moulding for classifying three wear states of a mould in operation (early run-in, production, worn-out). Figure 1 displays the six life-cycle stages of a mould at our industrial partner (left) and lists relevant data, including type and life-cycle stage from which we collect it (right). The stages most relevant for our contribution are: (1) Design, create and assemble the mould for a specific element design; (2) Run tests to find the optimal operating point and hand-over the mould to production; (3) Fulfill an incoming production order; (4) Continuously monitor element quality



Stage	Data name	Data type
1-6	Mould ID	Categorical (13)
1-6	Moulding Date	Year (2011-2020)
1-6	Number of Cycles	Numeric (0-15e^6)
1	Construction	Categorical (5)
1	Layout	Categorical (3)
3	Order Number	Categorical (503)
3	Machine	Categorical (17)
3	Screw Design	Categorical (6)
3	Production Site	Categorical (4)
3	Color	Categorical (29)
4	Metrology point	Categorical (12)
4	Measurement value	Numeric (*)
3, 5-6	Maintenance data	Free text

Fig. 1. Illustration of the six mould lifecycle stages at our industrial partner (left) and description of the data set (right). *Stage* labels the origin of the data. *Data type* describes attributes of the data: Categorical types include number of unique values; Numeric types include the range. *The range of measurement values depends on the specific metrology point.

by collecting samples; (5) Conduct planned and unplanned maintenance; and (6) Remove the mould from production. We refer the reader to Kazmer [8] for more details on mould design, element approval and mould maintenance.

The data set contains historic measurements of the same moulded element geometry produced using 13 different injection moulds. The *Mould ID* uniquely identifies a mould throughout its lifetime. The data was collected in a period of nine years from 2011–2020. Instead of associating events with a date, we use the *Number of Cycles* to quantify the age of a mould as a function of usage in production independent of time spent in storage, workshop etc. Five mould constructions and three mould layouts were included in our analysis. The data set contains additional information on single production orders i.e. *Order Number* as unique label, machine type (hydraulic, electric, or hybrid), design of the injection screw and production site. The raw material used in this study was ABS mixed with one of 29 different color additives.

Metrology Data. The produced element is a small rectangular box, with a supporting rip at the center on the long side (to reduce warpage). Figure 2 illustrates the element geometry and metrology measuring points. In total 10 measuring points including four specific measures are collected (length, width, height and wall thickness). The element metrology is sampled every three weeks. A quality sample consists of a batch of elements from each cavity of the mould from a single injection cycle. In total, the data set contains 17,203 element metrology samples per measurement point. To preserve data confidentiality, all metrology measures are scaled according to the specification limits provided by the industrial partner between **+1** (upper specification limit) and **−1** (lower specification limit) with **0** indicating the target value. Thus, positive values indicate elements larger than target and negative values indicate elements smaller than target. Elements above/below **+1/−1** are outside of specifications and are thus rejected.

ID (Positions)	Measurement
OH_x (1,7,9)	Outside Height
OL_x (1)	Outside Length
OW_x (1,2)	Outside Width
WS_x (1,8)	Side wall thickness
WL_x (1,4)	End wall thickness
WS_tot (WS_1+WS_8)	Sum of wall thickness
WL_tot (WL_1+WL_4)	Sum of wall thickness

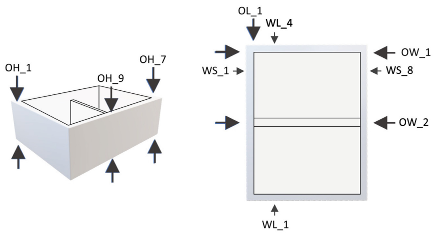


Fig. 2. Illustration of the moulded element and description of location of metrology measurements. WS_tot and WE_tot are calculated as the sum of the two wall thicknesses at the side positions and end positions respectively to reduce the impact of variations in the alignment of the two mould halves.

3 Exploratory Analysis of Maintenance and Metrology Data

A majority of the maintenance data is free text allowing detailed description of the problem/cause but interfering with an automated analysis. All free text entries are linked to one of 11 different root causes displayed in Fig. 3.

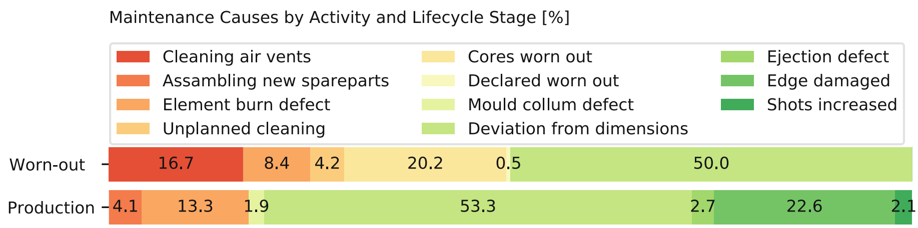


Fig. 3. Frequency percentage of 11 maintenance events by lifecycle stage. No maintenance was recorded in the early run-in period.

For both production and worn-out moulds, majority of maintenance are associated with deviation from dimensions of the elements (53.3% and 50.0% respectively). Followed by edge damage (22.6%) and burn marks (13.3%) for production moulds and cores worn-out (20.2%) and cleaning of air vents (16.7%) for worn out moulds. In the following analysis we focus on the factor with greatest impact i.e. deviation from dimensions.

Due to mould wear and degradation, we expect the different metrology measures to change over time. When introduced into production, injection moulds can have dissimilar dimensions due to the tolerances of upstream manufacturing processes. Consequently, initial element dimensions vary from mould to mould. Thus, to investigate mould degradation across moulds we align the metrology measurements by subtracting the average values for individual mould/cavity/metrology measure combination for the first 2.000.000 moulding cycles from the same mould/cavity/metrology measure combination. Our analysis indicates that for all moulds the height of the elements decreases with cycle count. Further, our analysis shows that the element wall thickness and length increases as function of cycle count. We show the change of element height (OH_7), wall thickness (WS_tot), outside width (OW_2) and (OL_1) for three illustrative moulds (Fig. 4) due to the large size of the entire data set. As shown, both element height and wall thickness (Fig. 4B and Fig. 4D) exhibit a consistent downward and upward trend respectively. The outside width (Fig. 4C) indicates a marginal positive slope resulting in wider elements. This can be the result of progressive compression of the mould parts in clamping direction reducing element height and abrasive material loses from cavity walls, and core surfaces increasing the wall thickness. While we expected a similar increasing trend for the element length due to abrasion of the cavity walls, Fig. 4A displays a steep positive slope for one mould, and a negative slope for the other two. Our analysis of metrology data shows the height of the elements and the wall thickness give the most consistent indicators of mould degradation.

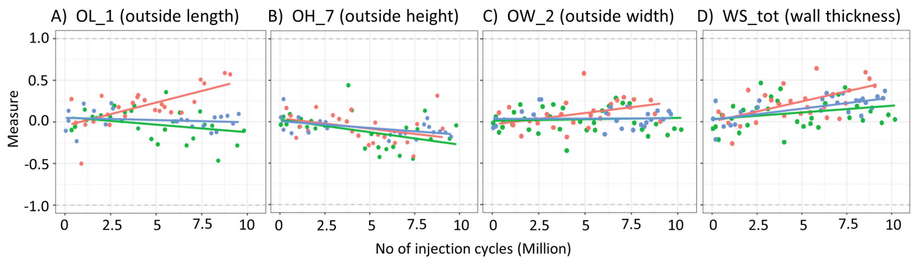


Fig. 4. Change in metrology measures by mould age (number of injection cycles) for three randomly selected moulds.

4 Monitoring of Mould Worn-Out Using MSPC

Section 3 shows specific element dimensions can be used as proxy for analyzing mould degradation. One of the most common methods for monitoring process quality (i.e. deviation in element dimensions) is using control charts [9]. Instead of monitoring the 12 metrology measures individually, we apply Multivariate Statistical Process Control (MSPC) with the quality measures reduced to latent variables using Principal Component Analysis (PCA) (see MacGregor et al. [10]) for systematically tracking element dimensions and thereby degradation of moulding parts in a single control chart. Based on the latent variables, we derive Hotelling T^2 for monitoring the matrix of the latent variables and Q-statistics for monitoring the residuals.

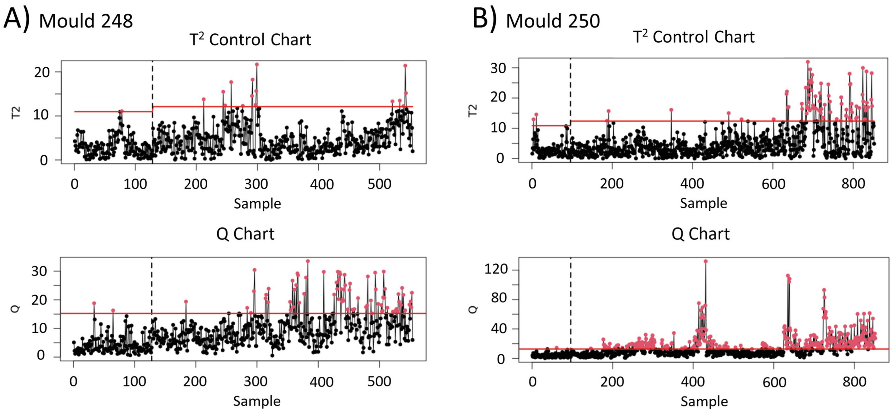


Fig. 5. MSPC for the two moulds declared worn-out due to deviations in dimensions. Samples from the initial 2.000.000 cycles were used to create the baseline model.

Even though element dimensions were the largest contributor to maintenance actions, the actual cause of disposal was only recorded for a small fraction of moulds in the data set. However, to verify the applicability of element quality measures for monitoring mould degradation, our analysis required moulds that were marked as worn-out due to element dimensions being out of specifications. Only two such moulds (Mould ID 248 & 250) were present in the data set. Therefore, we selected these moulds for demonstrating the applicability of MSPC and creating the relevant control charts. The Hotelling T^2 and Q statistic for these molds and control limits (the solid red lines) are shown in Fig. 5.

The control charts enabled monitoring the degradation of the moulds linked to elements being out of dimensions. Mould 248 was declared worn-out between sample 450–550. As show in Fig. 5A, the Hotelling T^2 indicates an out of control behaviour in this sample range. For mould 250 the T^2 chart in Fig. 5B implies fairly constant element dimensions (and correlation between dimensions) for the first 500 samples. From approximately sample 500, variation in T^2 is increasing. From sample 650 the first indication of worn-out is present as T^2 surpasses the control limit. The corresponding Q chart implies an out-of-control situation after sample 400 indicating a change in the model residuals. This can be due to changes in the part of the correlation structure not included in the selected latent variables. Situations like this have to be investigate before a more widely implementation of a MSPC solution. Further, for Mould ID 248 the control limit is exceeded between sample 250 and 300 on the T^2 chart shown in Fig. 5A. The free text in the maintenance data describes that shortly after sample 300 cavity inserts were change due to element dimension being outside of the specification limits. Using the T^2 chart an early indication of the insert worn-out could have been realized at sample 250. The Q chart in Fig. 5A shows that the model residual change after assembling of new insert parts. Thus, the underlying PCA model requires updating to account for variations introduced by changing the inserts. The above results from the two moulds indicate that MSPC is applicable for monitoring element dimension and that the variation seen in the T^2 charts can be linked to mould degradation.

5 Classification of Mould State

To extend the results in Sect. 4 and investigate mould degradation for all moulds using metrology measures, we develop a classification model with the wear states labelled early run-in, production and worn-out. Based on expert input from the industrial partner, we define the early run-in state as the first 30% of the collected samples, production as samples collected between 30–80%, and worn-out as the samples collected above 80% of the maximum cycle count for a mould. Partial Least Squares - Discriminant Analysis (PLS-DA) [11] and *XGBoost* [12] were tested on two different data sets, one being the 12 metrology measures (compare Fig. 2) and one being the 12 metrology measures combined with five selected categorical features (Construction, Production site, Screw, Colour and Machine). We choose PLS-DA since PCA captured the latent structure related to worn-out and XGBoost as it is a tree-based method performing well for a data-set with both numerical and categorical features. The categorical features were introduced in the data set by converting them to dummy variables and applying PCA for reducing them to ten latent variables (explaining 94% of the total variation). The XGBoost model using the metrology data combined with the latent representation of the five categorical variables shows the best performance among the four models i.e. PLS-DA with and without latent variables, XGBoost with and without latent variables. The results indicate that while the discrimination between early run-in and production achieves only a within-class accuracy of 73% and 61% respectively, the worn-out class achieves accuracy of 88%. In comparison, the XGBoost model excluding the latent variables leads an accuracy of 74% for the worn-out class. Further, the two PLS-DA models achieve an worn-out class accuracy of only 30% with and 35% without latent variables. Distinguishing between early run-in and production class is not critical, as detection of the worn-out state.

6 Discussion and Conclusion

This paper used real-world production data to develop data-driven models capable of detecting long-term degradation of plastic injection moulds. Analysis of metrology measurements from the industrial data set confirmed that dimensions of moulded elements changed systematically over time. This can be explained by degradation of moulding parts (compression of moulding parts resulting in reduced height of the elements, abrasion of material from the walls in the cavities and on the cores, resulting in longer and wider elements with thicker walls).

Based on these findings two different approaches were explored for monitoring degradation progression and detecting worn-out moulds (utilizing metrology data). Results show that an MSPC-based approach can be used for monitoring mould degradation and for supporting decisions related to change of inserts/cores and declaration of mould wear-out. Additionally, our results demonstrated that fairly accurate identification of remaining useful life of the mould (based on mould state classification) is possible using element metrology and a latent representation of key categorical variables. Both PLS-DA and XGBoost were tested as classifiers and XGBoost was found to be superior achieving a within-class accuracy of 88% for the worn-out class.

The results in this paper can be used for supporting and scheduling of mould maintenance. Further, they create a foundation for developing solutions for mould monitoring and decision support on when to perform a mould worn-out evaluation. We expect that collection of additional time series data such as machine and process data form the moulding machines can help to distinguish variation in the metrology measures due to material/process variations and degradation of mould parts.

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