Quality Prediction of Molded Products with Machine Learning Using In-mold Sensing Information

Y. OKUBO S. HAGIHARA S. MIZOGUCHI T. BABA T. ADACHI

A method for predicting the quality of plastic products produced by injection molding using sensing data obtained inside molds and machine learning was proposed, and its effectiveness was verified by comparing predicted and experimental results. Technology to modify molding conditions automatically was then developed based on the obtained predicted results.

***Key Words**: quality prediction, machine learning, in-mold sensing information*

1. Introduction

In recent years, with accelerating global-scale efforts and ESG investment aimed at sustainable development targets, the importance of environmentally friendly manufacturing is growing. In the automobile industry, in addition to the development of electric vehicles and fuel cell vehicles, part weights are being reduced in order to improve fuel economy, and the change from metal parts to plastic parts is accelerating.

In the injection molding process for ordinary plastic parts, external factors can change the melt viscosity and alter the molding results. For this reason, the operator adjusts the molding conditions as necessary in order to maintain quality, and that quality is affected by the operator's level of experience. For this reason, from the perspective of stabilizing quality that is not dependent on the level of experience, studies are proceeding for making the molding machines themselves more intelligent. For example, Shioiri *et al*. have constructed a technology for predicting quality in the injection molding process using information such as the molding conditions and a neural network[1]. While it is known that molding quality is highly dependent on factors such as the plastic flow behavior inside the mold[2], because mold shapes vary widely depending on the part being molded, the plastic flow behavior is not always the same, and obtaining universal knowledge is difficult. For this reason, there are currently few studies related to quality predictions using information from inside the mold.

This report constructs a quality prediction method for molded products using machine learning and various information from the molding process, including in-mold sensing information. As one example of injection molded products, this method is applied to the mass and inner diameter of the ball bearing plastic retainer (**Fig. 1**) that is an important JTEKT product. It also verifies the effectiveness of this method by comparing the prediction results and actual measured results for the mass and inner diameter. Furthermore, we attempt to automatically modify the molding conditions using the prediction results in order to stabilize quality. In plastic molding, air remaining inside a molded product may produce a phenomenon known as "voids," which may lower the strength of a functional part and may result in fracture. In order to accurately determine whether or not these voids are present, an X-ray CT method is effective, however this measurement requires a long time and it is not practical to measure all molded products. Therefore this study uses the molded product mass as a substitute quality index for void management. The inner diameter is a quality index for managing the required dimensional tolerances.

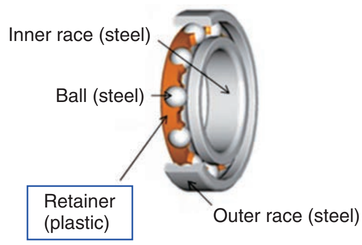


Fig. 1 Ball bearing components

2. Study of a Quality Prediction Method

2. 1 Necessity of In-mold Sensing Information

It is known from previous studies[2] that molding quality is highly dependent on the plastic flow behavior inside the mold. For this reason, it is considered possible to predict quality with high accuracy by using information about plastic conditions inside the mold during molding.

2. 2 Use of Machine Learning

It is known that molten plastic during the molding process exhibits non-linear behavior typified by its PVT properties. PVT properties are properties which change the plastic specific volume (units: cm^3/g) according to the plastic temperature and the applied pressure. Furthermore, because plastic changes from molten to solid in a short time during the molding process, it is expected that its temperature and viscosity also change rapidly. In consideration of this point, the use of a machine learning method that can consider non-linearity is considered to be effective for quality predictions.

In order to achieve high accuracy quality predictions, we studied a quality prediction method using in-mold sensing information and a machine learning method that can consider non-linearity.

3. Machine Learning

3. 1 Selection of a Method

Prediction of the mass and inner diameter requires predicting continuous values, and is classified as a regression problem in machine learning. Typical machine learning methods that can be applied to regression analysis are shown in **Table 1**. Regression analysis methods are broadly divided into linear regression methods and non-linear regression methods. Because each method has its own characteristics, it is necessary to select a method according to the purpose. For example, when using an approach that requires a large volume of data such as with a neural network, at the trial stage in manufacturing or other industry, the small amount of available data may result in insufficient accuracy. Therefore in this study, we used Support Vector Regression (hereafter "SVR") for two reasons: first that it can consider non-linearity as mentioned in **Section 2. 2**, and second that it can be expected to produce high prediction accuracy with a relatively small volume of learning data[3].

Table 1 Typical regression analysis methods

	Method Name	Characteristic
Linear Methods	Simple Regression	Easier interpretation of result
	Multiple Regression	Easier interpretation of result
	Ridge Regression	Prevent overfitting
Non-linear Methods	Support Vector Regression	High accuracy with relatively few data
	Random Forest	High accuracy with relatively few data
	Neural Network	Very high accuracy with much data

3. 2 Overview of SVR

SVR uses a kernel method to achieve modeling that considers non-linearity. A kernel method is a method of linear modeling in a non-linear space by performing high-dimensional non-linear conversion of the feature vectors contained in the learning data. SVR is learning that aims to minimize Formula (1).

$$E(w) = \frac{1}{2}\|w\|^2 + C\sum_i |y_i - f(x_i)|_\varepsilon \tag{1}$$

However,

$$|y_i - f(x_i)|_\varepsilon = \max(0, |y_i - f(x_i)| - \varepsilon) \tag{2}$$

Here, y_i and x_i are data of number i that is used in learning. w is the weight vector; ε is the error threshold value; and C is a coefficient that adjusts the weighting between the two terms. Minimizing Formula (1) achieves non-linear modeling that balances suitability for the learning data with generalization performance. The kernel function used in the kernel method uses the Gaussian kernel shown in Formula (3).

$$K(x, x') = e^{-\gamma\|x-x'\|^2} \tag{3}$$

ε, C, and γ are coefficients that must be optimized according to the features of the learning data. In this study, they were decided using a method known as "grid search." Grid search systematically and comprehensively moves each coefficient a little at a time while calculating, and selects the combination which has the highest calculated accuracy. Because this method is intuitively easy to understand, it is widely used in the machine learning community[4].

4. Test Method

4. 1 Collection of Molding Data

Injection molding tests were conducted using an SR100H (product of Sumitomo Heavy Industries) as the molding machine, and polyamide material reinforced with glass fibers as the plastic material. Here, in order to identify the plastic conditions inside the mold during molding, pressure sensors and infrared detection-type temperature sensors were installed inside the mold to measure pressure and temperature. The layout of the sensors installed inside the mold is shown in **Fig. 2**. An example of the measurement results from the installed pressure sensors is shown in **Fig. 3**. Measurement was started using molding machine injection start as the trigger, and a pressure history was obtained for the filling, holding, and cooling processes at the weld, gate, runner, and nozzle. To obtain quality data of the molded product, an electronic scale and profile measurement machine were used to measure the mass and inner diameter.

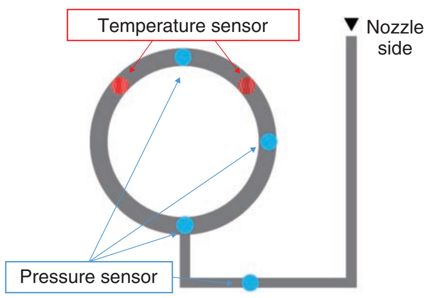


Fig. 2 Sensor layout

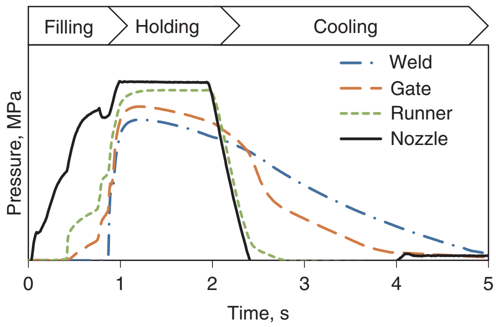
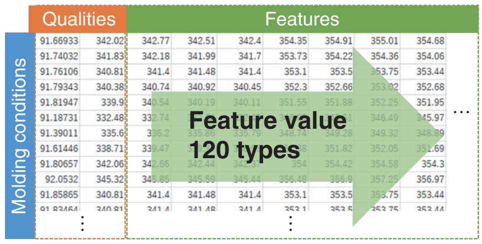


Fig. 3 Sensing data inside the mold

4. 2 Creation of Features and Dataset

Generally when handling time-series data as learning data for machine learning, the characteristic parts of the data are extracted and identified as features in order to improve the learning model accuracy and learning efficiency. In this study, 120 types of features, including maximum values and integrated values of specific ranges, were created from the pressure and temperature histories acquired by the sensors installed inside the mold. By associating these features with corresponding quality data, they were consolidated as a learning dataset (**Table 2**).

Table 2 Dataset



4. 3 Selection of Important Features

With a machine learning method that uses regression analysis such as SVR, overfitting is less probable to occur when there is a smaller number of explanatory variables used in learning[5]. In the fields of statistics and machine learning, overfitting is a phenomenon that significantly lowers prediction accuracy when the prediction is excessively tailored to the data that was used for learning, reducing its suitability for use with unknown data. Therefore in order to avoid overfitting, it is preferred that the optimal explanatory variables be selected using knowledge and expertise based on molding theory and experience. However when handling a complex phenomenon such as plastic molding, it is not easy to select suitable variables based on an understanding of all plastic flow behavior.

Therefore in this study, we considered a data-driven solution to this problem. Specifically, we attempted to use statistical methods to automatically select key features using quality data as the objective variables, and the many features created in **Section 4. 2** as the explanatory variables. A standardization process was performed for each data, and the weighting between features was handled equivalently.

Many algorithms have been proposed for automatic selection of features using statistical methods, including a regression model type[6] and graphical model type[7]. However there are no judgment indexes for determining which algorithm is suitable in which cases, and in most cases the algorithm is selected based on experience. However each algorithm has suitability depending on the target data, and caution is required because the installed algorithm will not always produce valid solutions. In order to resolve this issue, in this report we considered logic that made combined use of multiple algorithms. An overview of the process used for selection of features is shown in **Fig. 4**. The four algorithms that were used are shown in **Table 3**. The characteristics of each algorithm are as shown below.

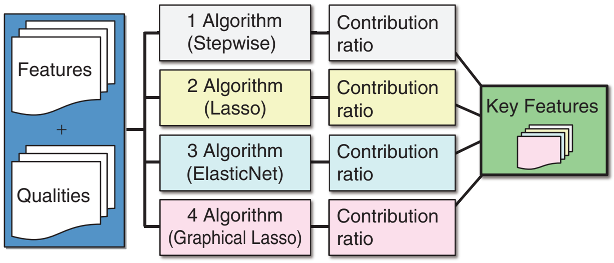


Fig. 4 Process for feature selection

Table 3 Statistical method algorithms

Algorithm	Loss function
Stepwise	$\mathit{argmin}\ \varepsilon(w)=\sum(y-Xw)^2$
Lasso	$\mathit{argmin}\ \varepsilon(w)=\sum(y-Xw)^2+\lambda\sum\lvert w\rvert$
ElasticNet	$\mathit{argmin}\ \varepsilon(w)=\sum(y-Xw)^2+\lambda\sum\{\alpha\lvert w\rvert+(1-\alpha)w^2\}$
Graphical Lasso	$\underset{\Lambda}{\mathit{argmax}}\{\ln\det\Lambda-\mathrm{Tr}(S\Lambda)-\rho\lVert\Lambda\rVert_1\}$

(1) Stepwise[8)]

This is a regression method that searches for the optimal combination of explanatory variables while adding or removing explanatory variables to/from the learning model one at a time. This method has the disadvantage of the learning model estimations becoming unstable when there are groups of explanatory variables that have strong correlation.

(2) Lasso[6)]

This method adds an L1 regularization term to a regression model. Regularization allows this algorithm to avoid the Stepwise disadvantage described above. L1 regularization has the property of producing sparse solutions, and this property enables the automatic selection of variables. However it has the disadvantage of being able to select only a single variable when there is a group of explanatory variables that have strong correlation.

(3) ElasticNet[9)]

The regularization term is characterized by using the sum of the L1 norm and L2 norm. Because this has the effect of grouping explanatory variable groups that have strong correlation, this method is able to avoid the disadvantage of Lasso.

(4) Graphical Lasso[7)]

This method introduces sparsity into a Gaussian graphical model. The approach is different from that in (1) to (3), and it is characterized by identifying correlation between variables while eliminating spurious correlation.

After calculating the degree of contribution to quality of each feature using the four algorithms in the process shown in **Fig. 4**, the calculation results from each are combined in order to automatically select the features to input into SVR.

5. Quality Prediction Results and Considerations

Here, in order to verify the validity of the aforementioned quality prediction method using in-mold sensing information and a machine learning method that can consider non-linearity, we compared the determination coefficients that were calculated from the prediction results and actual measurement results for mass and inner diameter. We also attempted to automatically modify the molding conditions based on the prediction results in order to stabilize quality.

5. 1 Comparison of Prediction Results with and without In-mold Sensing Information

The prediction results for mass and inner diameter with and without in-mold sensing information are shown in **Fig. 5**. **Figure 5** shows that the use of in-mold sensing information improved the determination coefficient for mass and inner diameter from 0.86 to 0.9 and from 0.8 to 0.93 respectively. As theorized in **Section 2. 1**, it is assumed that this is because the molding condition settings deviated from the actual plastic flow behavior, and that the information obtained from sensors installed inside the mold is closer to the actual phenomenon.

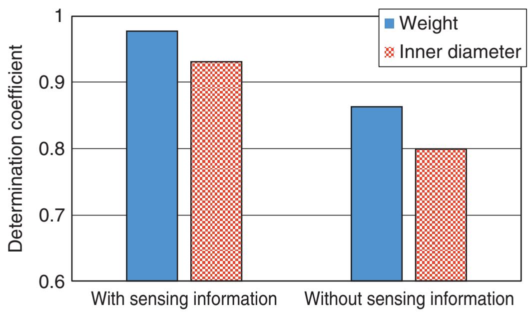


Fig. 5 Comparison of the determination coefficients with and without sensing information

5. 2 Comparison of Prediction Results with and without Machine Learning

Next the prediction results for mass and inner diameter based on in-mold sensing information when using the machine learning non-linear regression method SVR and when using a classical multiple linear regression analysis method are shown in **Fig. 6**. **Figure 6** shows that the use of the machine learning non-linear regression method SVR improved the determination coefficient for mass and inner diameter from 0.91 to 0.98 and from 0.8 to 0.93 respectively. This is presumed to be because it was able to approximate the non-linearity of the plastic

PVT properties and the cooling process. Because it is extremely difficult to clarify all of the mechanisms related to this plastic non-linearity, the use of a machine learning method that considers non-linearity is considered to be effective, as theorized in **Section 2. 2.**

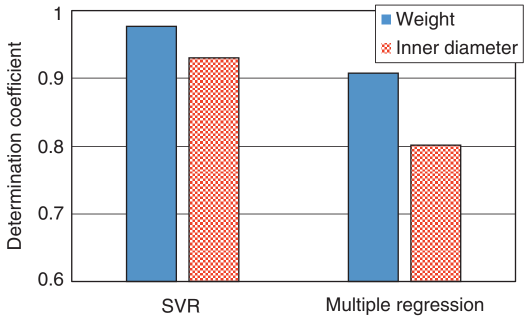


Fig. 6 Comparison of the determination coefficients between SVR and multiple regression

5. 3 Automatic Modification of Molding Conditions

This section describes automatic modification of molding conditions to stabilize quality using the quality prediction method studied in this report. The architecture of the system is shown in **Fig. 7**. It automatically modifies molding conditions based on the differences between the predicted value and target value for mass and inner diameter in order to approximate the measured results to the target values. First, the pressure and temperature histories obtained for each molding are converted to features, and sent to the calculation server. When the features are received by the server, the learned model is used to predict quality. After the amount of molding condition modification is calculated based on the differences from the target values, the molding machine settings are automatically adjusted. A history of the measurement results for mass and inner diameter when the molding conditions were automatically modified using this system is shown in **Fig. 8**. In order to check the performance of this system, the quality value was forcibly deviated from the target value before performing automatic modification. The figure demonstrates that automatic modification of the molding conditions caused both mass and inner diameter to converge on the target values. Therefore this shows there is the possibility of applying the studied quality prediction method to automatic modification of molding conditions.

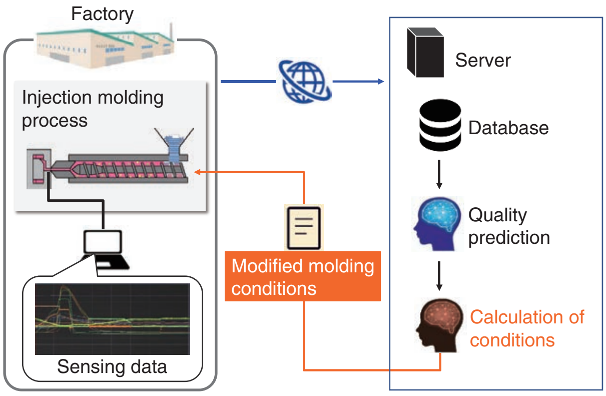


Fig. 7 Architecture for automatic modification of molding conditions

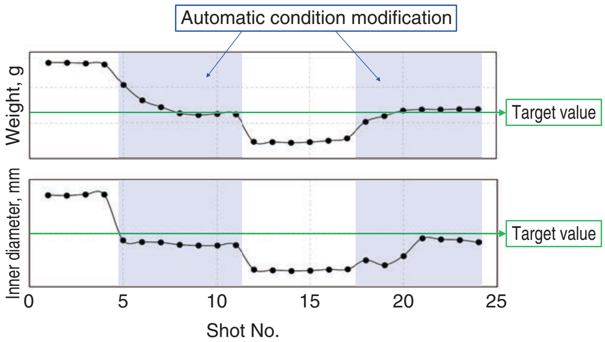


Fig. 8 Measured results of weight and inner diameter under automatic molding

6. Conclusion

In this report, we constructed a molded product quality prediction system for mass and inner diameter of the ball bearing plastic retainer using in-mold sensing information and machine learning. Incorporating in-mold sensing information into learning by the machine learning model improved the determination coefficient, which indicates the degree of consistency between the prediction result and measurement result, for mass and inner diameter from 0.86 to 0.98 and from 0.8 to 0.93 respectively. In addition, the use of the machine learning non-linear regression method SVR improved the determination coefficient for mass and inner diameter from 0.91 to 0.98 and from 0.8 to 0.93 respectively compared to a classical linear regression method. Furthermore, the results from an attempt to automatically modify the molding conditions using this method showed the potential for its application.

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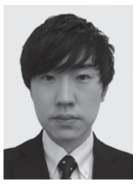

Y. OKUBO* S. HAGIHARA* S. MIZOGUCHI*


T. BABA** T. ADACHI**

* *Data Analytics R&D Dept., Research & Development Division*

** *Material R&D Dept., Research & Development Division*