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Paper:

Statistical Modelling of Machining Error for Model-Based Elastomer End-Milling

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Elastomer end-milling has attracted attention for use in the small-lot production of elastomeric fragments because the technique is an applicable method for a large variety of materials and does not require the preparation of expensive and time-consuming moulds. In order to effectively utilize elastomer end-milling, it is necessary to ensure the machining accuracy of elastomeric parts machined through this technique. However, the control method of machining error in the elastomer end-milling has not been presented since most machining services of the elastomeric part are based on enterprise-dependent dexterities or know-how. The objective of this paper is to construct and utilize a machining error model for elastomer end-milling. A statistical model based upon physical states and machining conditions is introduced and investigated. In this paper, a framework for modelling the machining error in elastomer end-milling is also proposed. In the framework, the candidates of model variables are evaluated based on the preliminary experiments. Moreover, a statistical model is constructed by using the selected variables. Candidate variables are cutting conditions and predictable physical state variables such as workpiece deformation and cutting force. The framework is investigated by evaluating error prediction with the experimental results. An identified error model from limited machining cases can estimate the machining error of different machining cases. The results indicate that the proposed modelling method is capable of supporting to achieve model-based precision elastomer end-milling.

Keywords: elastomer end-milling, machining error, statistical modelling, machining conditions

1. Introduction

Under the ongoing evolution of the digital age competition, appropriate manufacturing is increasingly required. In order to support the advanced production circumstances, there are many types of adaptations such as the functional material, continuously improved cutting tools, and newly developed mechanisms [1] which are applied technically. However, there will be a significant effect on the cost of the production. Repetitive manufacturing of the parts and components with complex shapes require time and cost consuming moulds. On the other hand, product prototyping or non-mass product, such as make-to-order production, needs to utilize machining methods [2, 3]. Particularly in a small-lot production of elastomeric parts, a reliable and accurate production method is eagerly desired [4, 5]. In order to guarantee essential quality indexes such as surface roughness and machining error, a prediction model is highly required to reduce the cost and time of machining [6, 7]. The modelling of machining operations has been evolving as an essential engineering tool to simulate operational physics ahead of costly production trials of parts used in industry [8].

In order to achieve the appropriate machining, a model-based approach is widely desired to become an alternative to a conventional trial and error approach concept. For these reasons, the prediction models are continuously developed and evaluated by comparing the predicted machining error with experimental results. Previously, a compositional machining simulation framework was proposed for model-based precision machining [9–12]. Because the standard metal machining processes are planned by assuming rigid workpiece and ideal chip removal, it is difficult to apply for elastomer end-milling owing to its low rigidity and different fracture mechanism. Many studies have been conducted to predict the machining process, such as the analysis of workpiece deformation, chip separation, and cutting force, including soft materials [13–22]. A mechanistic approach model was recently proposed for predicting machining error in elastomer end-milling [23]. However, the proposed mechanistic approach requires the heuristic introduction of an empirical model. By utilizing the statistics, the sensational data were considered to construct the machining error model.

In this paper, a modelling method for the empirical model of complex machining phenomena is introduced as a continuing developed model using a statistical approach. In order to find the state value-mediated relations for both machining conditions and machining error, a hybrid modelling method that utilizes numerical simulations and statistical modelling is proposed and expected to find direct information for controlling such phenomena. The proposed modelling is evaluated by comparing the calculated machining error and actual measurement in elastomer end-milling.

2. Machining Error in Elastomer End-Milling

The machining error in the end-milling process has involved machining conditions, workpiece shape, and material removal characteristics. During the actual machining situation, workpiece shape and machining conditions such as depth of cut and width of cut vary according to the machining process [21–23]. Furthermore, tool rotation speed and feed rate are sometimes adjusted to find the appropriate conditions when the new cutting tool, workpiece material, and/or different workpiece shape has to be applied. Regarding the workpiece deformation, the elastic analyses and measurement in the elastomer end-milling have been investigated by a similar method for metal end-milling [16, 17]. However, there have been a limited number of studies on the elastomer shape transferring error because the elastomer chip separation mechanism is entirely different from the metal mechanism [20, 24].

In the conventional metal end-milling, cutting force during the end-milling is one of the dominant factors to machining error. The cutting force causes the workpiece deformation, thermal formation, machine tool deflection, and tool wear. On the other hand, most elastomers have low rigidity then the relationship between cutting force and machining error is considered a fundamental characteristic. The chip formation mechanisms of elastomers are moderately different from those of metal milling. Furthermore, the deformation of the workpiece dominantly affects the machining accuracy. These facts indicate that the problem to be tackled for the end-milling of soft objects or elastomers is to control the appropriate surface generation of the machined workpiece that can overcome by designing an optimized cutting tool shape and/or determining proper machining conditions. Because of the large variety of elastomer objects, it is necessary to develop a systematic method to aggregate empirical cases to generate a mechanistic model of the surface generation process. There is little knowledge of those factors that are dominant to the error and further knowledge is required. Therefore, a preliminary evaluation of the important factors is necessary [11].

Shih et al. [25] have reported that the extraordinary mechanical properties of elastomer, considerably enduring elongation and low thermal conductivity, are capable of affecting the chip formation during machining significantly. In other words, tool wear is not a dominant factor for elastomer end-milling. Meanwhile, it is reported that the accumulations of cutting heat and the influence of thermal effects are not a dominant factor of the error tendency [21]. Therefore, it is promising to improve the machining accuracy by considering the mechanistic surface generation model with the dominant factors such as cutting force, workpiece deformation, and machining conditions for elastomer end-milling.

Recently, the mechanistic model was applied for machining error in elastomer end-milling [23]. The mentioned model applied machining knowledge to the empirical model formulation. By proposing the mathematical model which reflects process knowledge, the offered model is applicable for skipping evaluating the complicated phenomena of elastomer [26–28]. Based on the empirically extracted factors to explain machining error for elastomer end-milling phenomena, a simplified error model that is able to apply to statistical analysis was introduced [12]. Regarding the empirical assumptions, the machining error can be formulated as a mechanistic model as follows:

$$\delta = \alpha_1 x + \alpha_2 y + \alpha_3 f_x + \alpha_4 f_y + \alpha_5 \frac{f_x}{x} + \alpha_6 \frac{f_y}{y} + \alpha_7 \quad (1)$$

where x and y represent the displacements of the neighborhood point, f_x and f_y represent cutting forces at a surface generation moment, and $\alpha_1, \ldots, \alpha_7$ are model coefficients, and δ is machining error.

The cutting forces have been normalized by an axial depth of cut. An approximate local stiffness of the workpiece is the fifth and sixth terms on the right side of Eq. (1). Because the displacements and the cutting force can be predicted before machining when the appropriate model parameters have been identified, machining error can be predictable. This mechanistic model is called *Alpha-model* in this study.

With this model, the essential variables are obtained from insight using human observations. This method can be achieved by human heuristics that cannot be confirmed in advance. For this main reason, it is necessary to establish a more systematic methodology to evaluate the candidates of the model variables. As the application of the statistical technique to the variables' evaluation, the principal component analysis (PCA) statistical method, used in exploratory data analysis and for making predictive models [29], is employed for analyzing the error model that related machining error and variables such as machining conditions (depth of cutting, width of cutting, feed rate of cutting, and rotational speed of spindle) and physical state values (cutting force and/or workpiece deformation). The correlation of machining conditions and physical state values with the machining error is considered from a statistical perspective that can be used to select the priority-related variables for a model formation. Based on this idea, a systematic model construction procedure is defined as follows:

1. Collecting candidates of model variables including machining condition and physical state values when considering an available process simulation.
2. Designing a preliminary experiment based on known characteristics of material and cutting tool within the capability of experiment load.
3. Evaluating candidates of model variables based on the preliminary experiment.

4. Formulating a process model using selected model variables.
5. Identifying the process model based on the preliminary experiment.
6. Utilizing the identified model to predict the machining under different situations from preliminary experiments.

3. Framework for Empirical Modelling of Machining Error

Based on the defined procedures, we propose a modelling framework to predict the machining error of elastomer end-milling. The frameworks involving the error prediction of complex physical phenomena for the manufacturing process are based on the previously proposed modelling concept [11]. The framework consists of two phases: the identification phase and the estimation phase. In the identification phase, limited preliminary experiments were utilized to identify the process model. The identifying model is used to predict actual machining situations that differ from preliminary machining experiments. In order to design preliminary experiments, certain knowledge of the characteristics of the workpiece material and the cutting tool is assumed, including the cutting force tendency, workpiece material characteristics, physical state values, and error generation mechanism. When a new material and/or cutting tool is employed, basic trials are necessary to grasp the characteristics. A schematic of the framework for identifying and utilizing the machining error model is illustrated in **Fig. 1**. The variations in workpiece materials and cutting tools are smaller than variations in machining conditions and workpiece shapes. Therefore, the framework was organized to achieve the versatility of various machining conditions and workpiece shapes.

In order to compensate for influences of machining case variations, state values, including cutting force, workpiece deformation, and machining conditions, are used for constructing the error model. Because the influence of workpiece materials and cutting tools are not considered in this framework, the parameter identification process is required when a new cutting tool and/or workpiece material is employed for the machining process. In the identification phase, as demonstrated in **Fig. 1(a)**, the simplified preliminary experiments with the specialized machining equipment [21] were executed. The instantaneous cutting force and workpiece displacement can be measured simultaneously under different machining conditions. Furthermore, a simplified workpiece enables the evaluation of the machining error easily. The fundamental studies on machining have applied both a computational FEM and the experimental approach. For an initial effort of cutting force simulation, a standard discrete cutting force model has been used. The conventional cutting force model assumes that total cutting force can be approximated as the sum of local cutting forces [22].

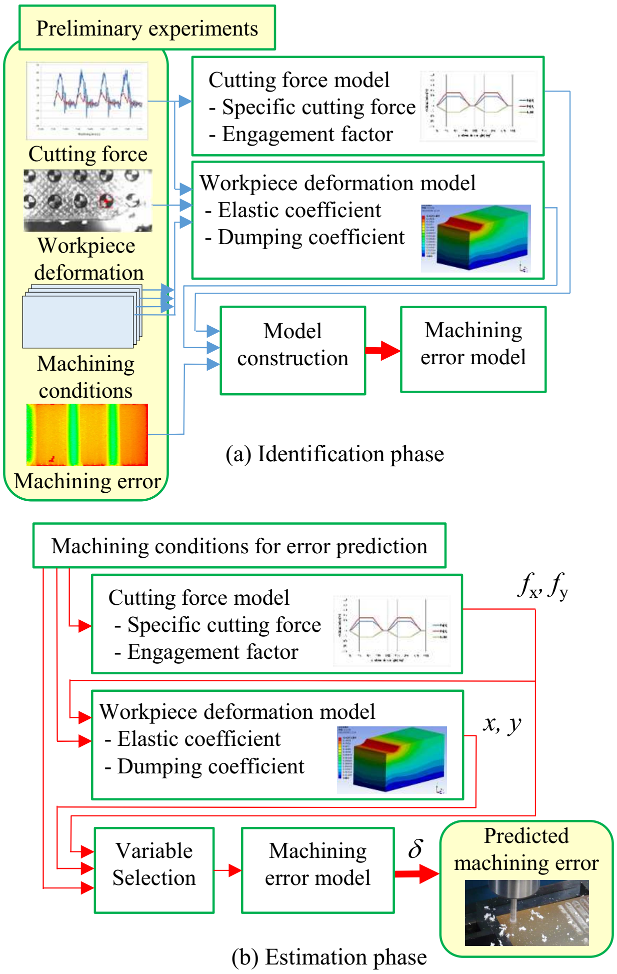


Fig. 1. Framework of machining error modelling.

The coefficients for the end mill are determined based on the average force-based determination method for cutting coefficients [30]. In order to investigate the error generation mechanism, measurements of the instantaneous workpiece deformation have been conducted. A quasi-two-dimensional cutting situation with a uniform fixture effect is constructed for machining. Image processing is employed to observe the actual displacements using a pre-calculated calibration scale and origin [21]. From the observation, the displacements obtained can be used to estimate the mechanical properties for a FEM analysis to simulate the workpiece deformation [28]. Based on previous research, the physical state values, such as the cutting force and workpiece deformation, can be calculated in principle. The model parameters for a deformation analysis and cutting force prediction were determined using the data obtained from preliminary experiments. The physical state values for every machining situation can be calculated using the identified process models. Machining conditions, physical state values, and their combined variables are the model variables of the machining error. By utilizing preliminary experiments, candidate variables were evaluated and selected. An empirical model of the machining error is constructed based on the selected variables. During the estimation phase, as shown in **Fig. 1(b)**, the machining error of the actual machining situations is reasonably calculated based on the selected model variables and the identified machining error model.

4. Evaluation of Framework of Empirical Model for Machining Error

4.1. Systematic Procedure of Evaluation Framework

In order to appraise the proposed framework, the cutting force model and workpiece deformation model must also be estimated in principle. However, the evaluation of a combined model becomes complex, and it is difficult to find the problem when estimation is not moderately appropriate. Hence, an independent evaluation of the machining error model is investigated as a fundamental evaluation of the machining error model. In case if the machining error calculated by the error model offers a good agreement with the measured machining error, the evaluation of the framework is equivalent to the evaluation of the cutting force model and workpiece deformation model that has been partially reported [21, 22]. Based on the independent evaluation of the machining error model, preliminary experimental data for the workpiece deformation and cutting force corresponding to the machining cases that are different from the parameter identification case are employed to calculate the machining error. **Fig. 2** illustrates an outline of the evaluation procedure for the error model. The candidates of the model variables are selected through a PCA analysis, and a machining error model is constructed as a linear model of the selected variables. The constructed error model coefficients are identified initially by the measured parameters, including the cutting force, the workpiece deformation, the machining conditions, and machining error. The responses of cutting force and workpiece deformation in the constructed model corresponding to the evaluation cases are substituted by the measured cutting force and the measured workpiece deformation. By comparing the estimated machining error and the measurement machining error, this error modelling is reasonably evaluated.

4.2. Experimental Setup and Configuration

In this stage, a high-speed steel endmill with a 6-mm diameter and a two-flute straight blade edged with a 20-μm roundness were applied on the machining center. Urethane rubber shore A90 hardness is employed as elastomer material because of its unique characteristics and mechanical properties. In addition, there are significantly difficult controlling chip separation and cutting phenomena [4, 5]. The experiments have been conducted according to our previous study [12, 23]. **Fig. 3** represents a schematic diagram of the configured experiment. The workpiece shape and the machining conditions are reasonably diversified and specified in **Table 1**.

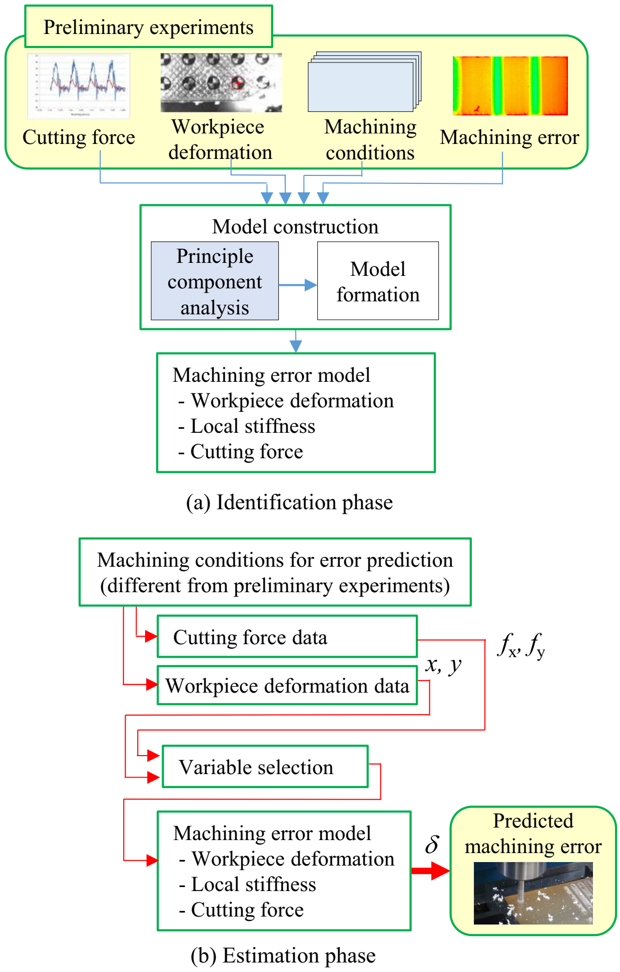


Fig. 2. Evaluation of machining error model.

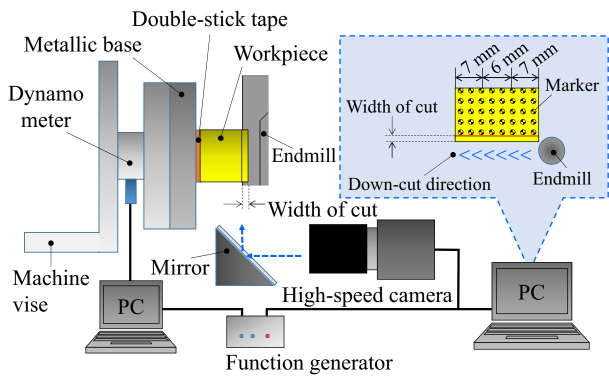


Fig. 3. Experimental configuration.

Concerning the experimental configuration, the workpiece stuck on a metallic base which is seized together with the dynamometer. The workpiece has been operated by the down-cutting method while a mirror is applied to observe the cutting behavior as a side view reflection during the machining process. Meanwhile, the workpiece deformation is monitored by the recorded moving images under the image processing method using a synchronized transmitting trigger signal from a function gen-

Table 1. Machining conditions.

(a) Preliminary experiments

Conditions	1	2	3	4	5	6
Machining direction	Down cut					
Width of cut (W) [mm]	1.0	0.5	0.7	1.0		
Depth of cut (D) [mm]	5.0	10.0				
Rotation speed (R) [rpm]	4000				2000	4000
Feed rate (F) [mm/tooth]	0.0125				0.025	
Workpiece width (A) [mm]	5.0	10.0				
Workpiece height (H) [mm]	10.0					20.0
Workpiece length (L) [mm]	20.0					

(b) Experiments for evaluation

#	W	D	R	F	$A \times H \times L$
1	0.3	10.0	4000	0.0125	10 × 10 × 20
2				0.0250	
3	0.5				
4			2000		
5	0.7		4000		
6	1.0	5.0		0.0094	5 × 10 × 20
7				0.0188	
8				0.0250	
9		10.0		0.0094	10 × 15 × 20
10				0.0125	10 × 10 × 20
11			2000		
12					10 × 15 × 20
13			4000		
14				0.0188	
15				0.0250	10 × 10 × 20
16					
17			2000		10 × 15 × 20
18			4000		
19				0.0094	10 × 20 × 20
20				0.0125	
21				0.0188	

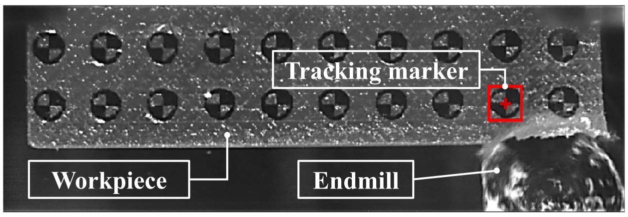


Fig. 4. Machining behavior observation.

erator and a high-speed camera. **Fig. 4** expresses the observation of the cutting behavior. A high-speed camera is employed to record workpiece deformations at the quasi-two-dimensional machining. From the recorded images, workpiece deformations at representative points are measured by using visual tracking of the marker.

A schematic of the machining error measurement is shown in **Fig. 5**. A non-contact laser displacement sen-

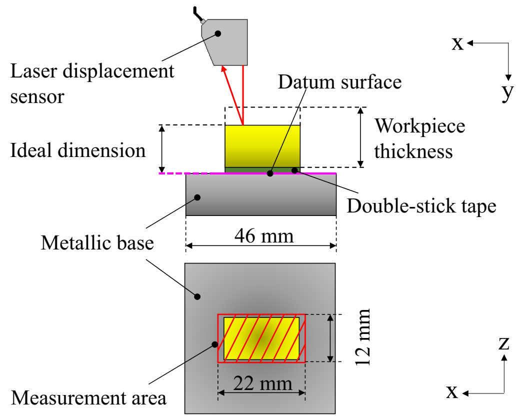


Fig. 5. Machining error measurement.

sor was utilized for measuring the machined workpiece surface. The average difference between the idealized surface and measured surface has been calculated. The synchronized measurement points are extracted corresponding to the machining error. The thickness of blank workpiece that is attached to the metallic base has been measured before machining. In preliminary experiments, the effects of the thickness of double-stick tape were evaluated and confirmed based on their stability and uniformity. The machined workpiece was removed from the dynamometer after machining and placed on the measuring equipment. Subsequently, a laser displacement sensor with a spot size of 70 micrometers was used to scan the machined elastomers. The surface of the metallic base was used as the reference (datum) surface for machining and measuring, as shown in **Figs. 3** and **5**. By comparing the before and after scanning thickness data of blank workpiece and machined surface, machining error has been estimated.

4.3. Evaluation of Machining Error Model

In order to evaluate the error model, machining experiments of an elastomer end-milling with diverse machining conditions were conducted to obtain the cutting forces, workpiece deformation, and machining error. In the overall machining cases, the machining direction is down-cutting. Preliminary experiments were initially conducted to obtain data for model identification. The primary machining conditions are specified in **Table 1(a)**. According to acquired cutting force, workpiece deformation, and machining error, the PCA is instructed to recognize the priority relations of the machining conditions and physics-based parameters that are important for constructing an error model. A PCA has become a dimensional reduction method for reducing the dimensionality of large datasets by condensing a set of variables into a smaller variable that preserves the amount of data. Although reducing the number of variables in a dataset decreases the accuracy, the method for achieving a dimensional reduction is to trade a slight amount of accuracy for simplicity. In this study, the following 18 components that can be utilized in

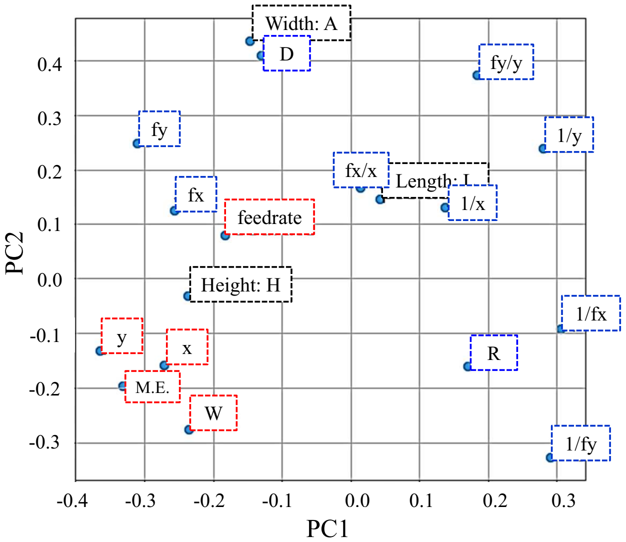


Fig. 6. Principal component response.

an actual experiment were evaluated. There are multiple numerical values to determine which parameters have a significant influence.

1. Machining error (M.E.).
2. Workpiece conditions: width (A), height (H), and length (L).
3. Machining conditions: rotational speed (R), feed rate (F), width of cutting (W), and depth of cutting (D).
4. Physical state values: displacement terms of neighborhood point; (x), ($1/x$), (y), ($1/y$) and cutting force terms at a surface generation moment; (fx), ($1/fx$), (fx/x), (fy), ($1/fy$), (fy/y).

Since some of the 18 variables have different units, a standardization of the experimental data is conducted to establish a certain standard that allows the numerical values between each condition to be used in common. Initially, standardization is employed as the first step of the PCA procedures. Then covariance matrix, eigenvectors, and eigenvalues are computed. The aim is to utilize the feature vector formed using the eigenvectors of the covariance matrix to reorient the data from the original axes to those represented by the principal components (PCs). The total contribution rate of each PC is equal to 1, and the data percentage can be rearranged. By ranking eigenvectors in order of eigenvalues, in descending order highest to lowest, the principal components in order of significance are obtained. **Fig. 6** shows a plot of the principal component scores by comparing the first and second PCs (PC1 versus PC2). From the PCA plotting, there are variations from every component in which the scores are not concentrated in one area, locally. The machining error is the target objective in which the principal component scores and eigenvector can determine that the influence-related variables are displacement y, x; width of cutting W; and feed rate F. Width, height, and length ($A \times H \times L$) are workpiece conditions that should be avoided when applying the error model to various workpiece shapes. Based on the PCA approach, the influential variables are selected, and the machining error model, called the Beta-model, can be formulated for the hybrid machining conditions and physics-based model as follows:

Table 2. Comparison of machining error results.

Proposed model	α	β
Difference of machining error [%]	24.18	14.79

$$\delta = \beta_1 x + \beta_2 y + \beta_3 W + \beta_4 F + \beta_5 \quad . \; . \; . \; . \; . \quad (2)$$

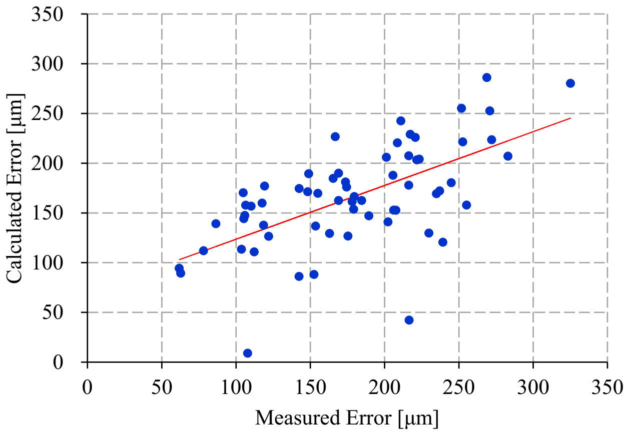
where x and y represent displacements of the neighborhood point, W represents the width of cutting, F represents the feed rate of the cutting, $\beta_1, \ldots, \beta_5$ are model coefficients, and δ is the machining error. Furthermore, the correlation coefficients and multiple regression analysis were applied to determine the coefficients of Eqs. (1) and (2), respectively.

Subsequently, the machining conditions that vary from the preliminary experiments were designed, as listed in **Table 1(b)**. Twenty-one machining condition cases were prepared to evaluate the machining operations. The measured cutting force and workpiece deformation acquired from the evaluation experiments were used to calculate the machining error as the estimated error. The estimated error can be compared with the measured machining errors. A comparison of the calculated (estimated) error results and measured error results of the mentioned evaluation experiments (21 conditions with 3 cases of each operation) is shown in **Table 2**.

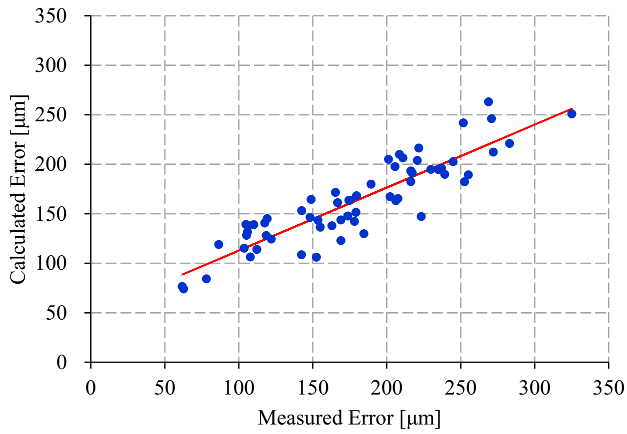
Table 2 presents a comparison of the machining error results between the mechanistic model (α) and the statistical model (β). The average differences between the measurement machining error and the estimation machining error of the proposed error models were approximately 24.18% and 14.79%, respectively. These results indicate that the proposed machining error models can be reasonably predicted when physical state values are appropriately predicted. **Fig. 7(a)** shows a comparison of the machining error results obtained from the mechanistic model. The error rates of both the maximum difference and distribution become large. **Fig. 7(b)** shows better agreement with the different machining error rate predictions than **Fig. 7(a)**, because the PCA-based variables selection has been considered by the significant variable component relationship.

5. Conclusions

In this paper, the statistical modelling of machining error was investigated for predicting the elastomer end-milling machining error by comparing the estimated machining error and the measured machining error. In or-



(a) Compared error of the mechanistic model



(b) Compared error of the statistics model

Fig. 7. Comparison of machining error of proposed models.

der to show the model results more clearly, the proposed mechanistic model and the proposed statistical model were reasonably compared. Systematic procedures were introduced as the modeling framework to construct and identify this error model. From the experimental evaluation, the feasibility of the proposed framework was confirmed. Using an appropriate statistical approach, it appropriately became possible to construct an effective error model without human insights. From the case studies of the machining error prediction, the proposed procedure can guide the construction of a suitable error model in the end-milling of the elastomer part.

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