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Research Article

Dimensional Deviation Estimation for Parts with Free-Form Surfaces

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Dimensional deviation is a prerequisite for improving the manufacturing process of parts with free-form surfaces, for example, the reverse adjustment of the die cavity of turbine blade. Influenced by random noise of the manufacturing process, dimensional variation is inevitable for batch parts. Therefore, it may cause unacceptable error to estimate batch parts dimensional deviation by a single sample. Meanwhile, the optimum sample size for estimating dimensional deviation is difficult to determine. To overcome this problem, a practical method for estimating of dimensional deviation of parts with free-form surface is proposed. Firstly, displacements of the discrete points on part surface are employed to represent dimensional error of the part. Estimating dimensional deviation of parts is actually to estimate the simultaneous confidence intervals of the discrete point displacements. Secondly, Bonferroni simultaneous confidence intervals are adopted to estimate the confidence intervals of the part dimensional deviation. Moreover, the accuracy of the estimation will be continuously improved by increasing samples. Consequently, a practical dimensional deviation estimation method is presented. Finally, a compressor blade is adopted to illustrate the proposed method. The percentage of estimation error of the blade dimensional deviation that is less than 0.05mm, which is the estimation error limit, of all the 100 times sampling experiments is 99%, exceeding the given confidence level of 95%, while the percentage of the existing method is below the confidence level, only 87%.

1. Introduction

With the development of technology and the improvement of manufacturing level, free-form surfaces are more and more applied in automobile, aerospace, and shipbuilding industries. Unlike regular geometric features, free-form surfaces can provide excellent mechanical properties, optical characteristics, fluid characteristics, and so on. Geometric shapes of parts with free-form surfaces are often closely related to parts' design performance [1, 2]. Meanwhile, dimensional accuracy will have a direct impact on parts' quality and performance [3]. However, manufacturing free-form surfaces is a highly complicated process [4]. Due to the influence of system errors and random noise of manufacturing process, dimensional deviation [5] and dimensional variation [6] are inevitable for batch parts. Dimensional deviation is the relative deviation of the dimension distribution center of the batch parts to its design dimension, which is the result of the system errors on parts' dimension. Dimensional variation refers to the discrete distribution state of the actual dimension of batch parts, which is the result of the random noise on parts' dimension. In recent years, the requirement of dimensional precision of free-form surfaces is higher and higher. Although some advanced techniques have been developed to solve the problem of design and processing, dimensional inspection of free-form surfaces is still a roadblock on the development of precision manufacturing [7].

Dimensional deviation plays an important role in the manufacturing process of free-form surface parts. As the comprehensive influence of the system error on parts' dimension, dimensional deviation is the essential prerequisite for evaluating or improving the manufacturing process. Taking the molded parts as an example, part dimensional deviation is the basis of the reverse adjustment of the mold cavity [8, 9]. However, it is impossible to measure all parts and then calculate its dimensional deviation due to the high cost.

In engineering, dimensional deviation is generally estimated by the inspection data of a set of parts. In theory, the more the samples, the more accurate the estimation of dimension deviation, meanwhile, the more the workload and cost [10].

In order to improve the efficiency of inspection, researchers have made great efforts to reduce inspection samples in the field of general industrial products. Khalifa et al. [11] carried out the extreme value and bootstrap methods to assess the localized corrosion of process components. The sample size that satisfies the given precision can be calculated by their method. Rodriguez-Verjan et al. [12] analyzed the defect inspection capacity planning when products were dynamically selected. They applied dynamic sampling method to the inspection process of semiconductor chip. The inspection efficiency was improved. Azadeh et al. [13] proposed a multistage optimization method based on particle swarm optimization. The total inspection cost was taken as the optimization objective of the algorithm, and the optimal test strategy was obtained. Fallahnezhad et al. [14] studied a new Bayesian sampling method based on cost objective function. They modeled the parts sampling error based on decision tree approach and optimal decision were determined. Tong et al. [15] researched a two-rank acceptance sampling plan for the inspection of geospatial data outputs based on the acceptance quality level which overcame the drawbacks of percent sampling. Abujiya et al. [16] studied the double ranked set sampling. Based on this sampling method, they then proposed an quality control chart for detecting changes in the process mean. Their method had a better performance compared with SRS and RSS. Peng et al. [17] discussed an acceptance sampling method for serial production system based on Markoff-based model. Jamkhaneh et al. [18] reported a single sampling method with inspection errors and fuzzy quality characteristics which solved the shortcomings of traditional sampling methods that assuming the population parameters are accurate.

Through the above literature analysis, it can be seen that, in the field of sampling inspection, scholars have done a lot of research work on sampling methods, such as resampling [19] and bootstrap sampling [20]. The estimation accuracy of the population statistics is improved, and the sample size can be reduced to a certain extent. However, free-form surfaces parts are more complicated than regular parts. Their dimensions cannot be described by a single number. In order to improve dimensional accuracy of free-form surfaces parts, the existing researches have mainly focused on the free-form surfaces machining methods [21–23] and measurement methods [24–28]. In fact, dimensional deviation estimation belongs to the mean value estimation problem. Under certain estimation accuracy requirement, the required sample size is directly related to the standard deviation of parts dimension. The greater the standard deviation, the greater the dimension variation of the parts, meanwhile, the more dispersed the dimension distribution of the same batch parts. This will lead to a more difficult estimation of parts' dimensional deviation. What is more, due to the fact that the free-form surfaces have complex geometric shapes and complex deformation which is difficult to be defined by precise mathematical formulae [29], at present, the sampling method of dimensional deviation estimation for free-form surfaces has not been reported yet.

Based on mathematical statistics, in order to estimate dimensional deviation of free-form surface parts, the following two problems need to be solved:

(1) How to quantify the dimension and deformation of free-form surfaces

(2) How to construct the pivot quantity of free-form surfaces to estimate its dimensional deviation.

This work tries to give a solution to the above two problems and propose a practical dimensional deviation estimation method for free-form surface parts. The organization of this paper is as follows: in Section 2, dimension description method for free-form surface parts is discussed. The sampling method oriented to dimensional deviation estimation of free-form surface parts is presented in Section 3. Case study is discussed in Section 4. Finally, conclusions and future work are discussed in Section 5.

2. Dimension Description Method for Free-Form Surface Parts

2.1. Dimension Analysis of Free-Form Surface Parts. In order to inspect free-form surface parts and infer its dimensional deviation, it is necessary first to quantify the free-form surface dimensions to construct statistics. However, free-form surfaces are more complex than the regular surfaces. In contrast to regular parts, dimensions of parts with free-form surfaces is difficult to be described by a single number.

Discrete points are a set of points with a specific relative position for describing the geometry of the surface. It can be seen from the surface design process that the discrete points are the basis of the surface design. Thus the coordinate value of the discrete points can be used to describe the dimensions of the free-form surfaces. In this work, a matrix composed of coordinates of discrete points is proposed to quantify the dimensions of free-form surfaces.

A free-form surface which is denoted as S and lofted by a sections is shown in Figure 1; each section is interpolated by b points. The coordinate of the point p_{jk} on k column from j row is (x_{jk}, y_{jk}, z_{jk}). Then the nominal dimensions of the surface can be represented by the coordinates of the b column points as shown in

$$S = \begin{bmatrix} p_{11}, p_{12}, \cdots, p_{1b} \\ p_{21}, p_{22}, \cdots, p_{2b} \\ \vdots \quad \ddots \quad \vdots \\ p_{a1}, p_{a2}, \cdots, p_{ab} \end{bmatrix} \tag{1}$$

The sketch map of deformation of the free-form surface S is shown in Figure 2. Surface S_i is the deformed model of surface S. Let $(p_{jk})_i$ represent the points on k column from j row of S_i. Assume the coordinate of $(p_{jk})_i$ to be

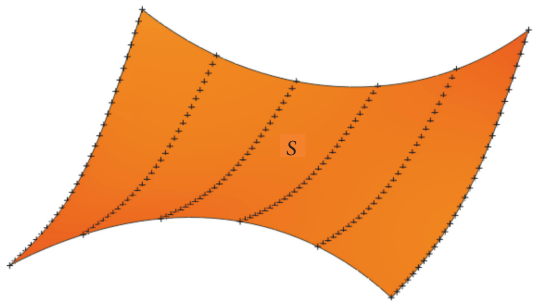


FIGURE 1: Free-form surface and its discrete points.

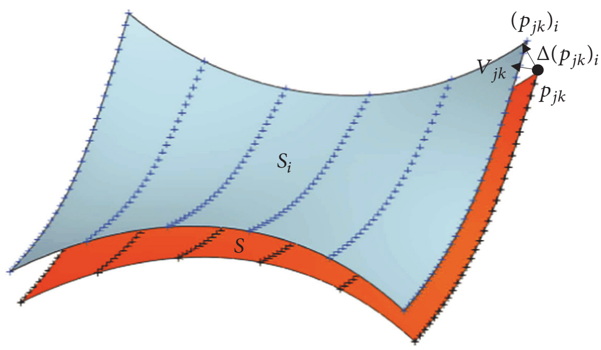


FIGURE 2: Deformation of free-form surface.

$((x_{jk})_i, (y_{jk})_i, (z_{jk})_i)$, then the displacement of point p_{jk} can be calculated by

$$g = \begin{cases} 0 & \text{if } \overrightarrow{\Delta\left(p_{jk}\right)_i} \cdot V_{jk} > 0 \\ 1 & \text{if } \overrightarrow{\Delta\left(p_{jk}\right)_i} \cdot V_{jk} < 0 \end{cases}$$
$$\left|\overrightarrow{\Delta\left(p_{jk}\right)_i}\right| = (-1)^g \cdot \sqrt{\left(\left(x_{jk}\right)_i - x_{jk}\right)^2 + \left(\left(y_{jk}\right)_i - y_{jk}\right)^2 + \left(\left(z_{jk}\right)_i - z_{jk}\right)^2} \quad (2)$$

with V_{jk} being the normal vector of the surface at point p_{jk}. Defining the deformation is positive when the angle between the displacement and the normal vector is an acute angle; otherwise it is negative.

Due to the influence of the systematic error and random noise in manufacturing process, the sketch map of deformation of free-form surfaces is usually as shown in Figure 3. That is, the actual surface of the batch parts has a certain dimensional deviation from the design surface and dimensional variation at the same time.

2.2. Definitions of Related Concepts. In order to facilitate analysis and description, four definitions are given as follows.

Dimensional error: it is the difference between the actual dimensions and design dimensions of surface parts. Matrix that is composed of displacement of discrete points, denoted

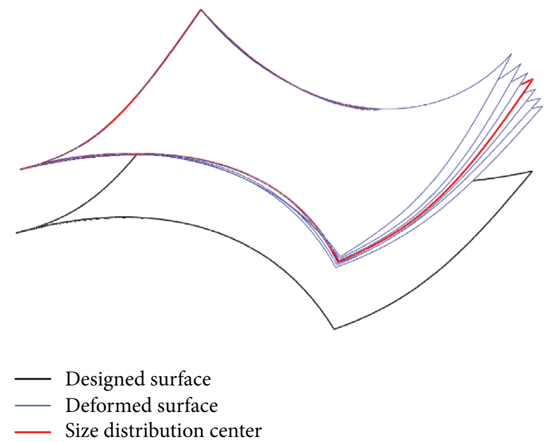


FIGURE 3: Sketch map of dimensional variation of free-form surfaces.

as ΔS, as shown in (3), is used to represent the dimensional error of surface parts.

$$\Delta S_i = \left|S_i - S\right| = \begin{bmatrix} \left|\overrightarrow{\Delta\left(p_{11}\right)_i}\right| & \left|\overrightarrow{\Delta\left(p_{12}\right)_i}\right| & \cdots & \left|\overrightarrow{\Delta\left(p_{1b}\right)_i}\right| \\ \left|\overrightarrow{\Delta\left(p_{21}\right)_i}\right| & \left|\overrightarrow{\Delta\left(p_{22}\right)_i}\right| & \cdots & \left|\overrightarrow{\Delta\left(p_{2b}\right)_i}\right| \\ \vdots & & \ddots & \vdots \\ \left|\overrightarrow{\Delta\left(p_{a1}\right)_i}\right| & \left|\overrightarrow{\Delta\left(p_{a2}\right)_i}\right| & \cdots & \left|\overrightarrow{\Delta\left(p_{ab}\right)_i}\right| \end{bmatrix} \quad (3)$$

with S_i as the actual dimensions of the ith part, S as the design dimensions of the part, and ΔS_i as the dimensional error of the part.

Dimensional distribution center: average dimension of batch surface parts is denoted as $\overline{S} = (1/N)\sum_{i=1}^{N} S_i$.

Dimensional deviation: it is the difference between the dimensional distribution center and the design dimensions of the batch surface parts.

Dimensional variation: it is fluctuation of the actual dimensions of the batch surface parts. For any point on the surface, the fluctuation can be measured by the variance of the deformation at that point. For any two points on the surface, the fluctuation can be measured by the covariance of the deformation of the two points.

In this section, a quantitative description method for the dimension and deformation of surface parts is proposed, which provides the basis of constructing the statistics and sampling for surface parts.

3. Proposed Methodology for Dimensional Deviation Estimation

The aim of this study is to narrow the dimensional deviation confidence interval of the batch free-form surface parts to the given precision according to the samples. The accuracy of sampling is usually measured by the absolute error or relative error in a certain probability and the probability here is called the confidence level.

Assume that the batch surface parts contain N individuals. Take n of them as samples, if the estimation error limit of the displacement of point p_{jk} is d_{jk} with the confidence level of $1-\alpha$. Dimensional deviation estimation of surface parts requires that the estimation error limit of all discrete points must satisfy (4) at the same time.

$$P\left\{\left|(\overline{p}_{11})_{sample}-(\overline{p}_{11})_{total}\right| \le d_{11},\cdots,\left|(\overline{p}_{ab})_{sample}-(\overline{p}_{ab})_{total}\right| \le d_{ab}\right\} \ge 1-\alpha \quad (4)$$

with α as the significance level. In this paper, $\alpha = 0.05$. That is the confidence level is not less than 95%.

From the above analysis, the estimation of dimensional deviation of surface parts is essentially to estimate the simultaneous confidence intervals of the displacement of all the discrete points on parts surface. Therefore, the estimation of dimensional deviation of surface parts can be transformed into multivariate statistical analysis and multivariate sampling problem.

In order to accomplish the accurate estimation of the dimensional deviation of surface parts, the estimation method for dimensional deviation interval of surface parts is given in the first part of this section. A novel sequential sampling method is proposed in the second part of this section.

3.1. Interval Estimation Method of Dimensional Deviation. Assume that the batch free-form surface parts contain N individuals. The ith part's displacement on point p_{jk} is $\Delta(p_{jk})_i$. $\Delta(p_{jk})_i$ can be calculated by

$$\Delta\left(p_{jk}\right)_i = \left(p_{jk}\right)_i - p_{jk} \quad (5)$$

The average of the displacement at point p_{jk} for the batch parts is $\Delta(\overline{p}_{jk})_{total}$. $\Delta(\overline{p}_{jk})_{total}$ can be calculated by

$$\Delta\left(\overline{p}_{jk}\right)_{total} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(p_{jk}\right)_i - p_{jk}\right] \quad (6)$$

The variance of displacement at point p_{jk} is $\sigma^2(p_{jk})_{total}$. $\sigma^2(p_{jk})_{total}$ can be calculated by

$$\sigma^2\left(p_{jk}\right)_{total} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(p_{jk}\right)_i - \Delta\left(\overline{p}_{jk}\right)_{total}\right]^2 \quad (7)$$

Affected by system errors and random noises, surface parts inevitably deform, which results in inaccurate dimensions or even out of tolerance. For constant systematic errors, the quality characteristics of the batch parts are regarded as approximately normal distribution [30, 31].

Assume that the average displacement of the samples at point p_{jk} is $\Delta(\overline{p}_{jk})_{sample}$. $\Delta(\overline{p}_{jk})_{sample}$ can be calculated by

$$\Delta\left(\overline{p}_{jk}\right)_{sample} = \frac{1}{n}\sum_{l=1}^{n}\left[\left(p_{jk}\right)_l - p_{jk}\right] \quad (8)$$

Displacement variance at point p_{jk} of the samples can be calculated by

$$\sigma^2\left(p_{jk}\right)_{sample} = \frac{1}{n-1}\sum_{l=1}^{n}\left[\left(p_{jk}\right)_l - \Delta\left(\overline{p}_{jk}\right)_{sample}\right]^2 \quad (9)$$

Then the following can be derived from the theory of mathematical statistics:

$$\frac{\Delta\left(\overline{p}_{jk}\right)_{sample} - \Delta\left(\overline{p}_{jk}\right)_{total}}{\sigma\left(p_{jk}\right)_{sample}/\sqrt{n}} \sim t\left(n-1\right) \quad (10)$$

The following can be obtained according to the quantile definition of t-distribution:

$$P\left\{\left|\frac{\Delta\left(\overline{p}_{jk}\right)_{sample} - \Delta\left(\overline{p}_{jk}\right)_{total}}{\sigma\left(p_{jk}\right)_{sample}/\sqrt{n}}\right| < t_{\alpha/2}\left(n-1\right)\right\} = 1-\alpha \quad (11)$$

with $t_{\alpha/2}(n-1)$ as quantile of t-distribution

Furthermore, the dimensional deviation interval with confidence level of $1-\alpha$ of point p_{jk} can be calculated by

$$\begin{aligned} &\Delta\left(\overline{p}_{jk}\right)_{sample} - t_{\alpha/2ab}\left(n-1\right)\frac{\sigma\left(p_{jk}\right)_{sample}}{\sqrt{n}} \\ &\le \Delta\left(\overline{P}_{jk}\right)_{total} \\ &\le \Delta\left(\overline{p}_{jk}\right)_{sample} + t_{\alpha/2ab}\left(n-1\right)\frac{\sigma\left(p_{jk}\right)_{sample}}{\sqrt{n}} \\ &\qquad i = 1,2,\cdots ab \end{aligned} \quad (12)$$

However, a surface is described by a set of discrete points. Only obtaining the displacement interval of a single point is far from enough. Therefore, the simultaneous confidence intervals in (4) are required for estimating the interval of dimensional deviation of the free-form surface parts.

Let the displacement of p_{jk} dropping into the interval in (12) be event C_{jk}. Obviously $P(C_{jk}) = 1-\alpha$. Thus the following can be obtained:

$$\begin{aligned} P\left(\bigcap_{j=1,k=1}^{j=a,k=b} C_{jk}\right) &= 1 - P\left(\bigcup_{j=1,k=1}^{j=a,k=b} \overline{C}_{jk}\right) \\ &\ge 1 - \sum_{j=1,k=1}^{j=a,k=b} P\left(\overline{C}_{jk}\right) = 1 - \sum_{j=1,k=1}^{j=a,k=b} \alpha \end{aligned} \quad (13)$$

The following can be derived from (13):

$$\begin{aligned}
&\Delta\left(\overline{p}_{jk}\right)_{sample} - t_{\alpha/2ab}\left(n-1\right)\frac{\sigma\left(p_{jk}\right)_{sample}}{\sqrt{n}} \\
&\quad \leq \Delta\left(\overline{P}_{jk}\right)_{total} \\
&\quad \leq \Delta\left(\overline{p}_{jk}\right)_{sample} + t_{\alpha/2ab}\left(n-1\right)\frac{\sigma\left(p_{jk}\right)_{sample}}{\sqrt{n}} \\
&\qquad j = 1,2,\cdots,a;\ k = 1,2,\cdots,b
\end{aligned} \tag{14}$$

It can be seen from (14), the larger ab, the smaller α/2ab. According to the nature of t-distribution, a large $t_{a/2ab}(1-n)$ indicates that more samples are needed to improve the estimation accuracy of $\Delta(\overline{P}_{jk})_{total}$. It also means greater workloads and inspection costs. In addition, according to (14), it should be stressed in particular that the standard deviation of point deformation can directly affect the estimation result of the point deformation. The greater the standard deviation, the greater . $\sigma(p_{jk})_{sample}$ in probability. Obviously, under the same estimation accuracy requirement, more samples are needed.

Therefore, it is necessary to control the number of discrete points in (14) to reduce samples and improve efficiency. This paper proposes a method to reduce the number of discrete points by selecting key points and constructing the Bonferroni simultaneous confidence intervals [32].

Through the inspection data of selected samples, displacement variance of all the discrete points can be obtained. The points with local maximum displacement variance can be regarded as the key points and used to reflect free-form surface dimensional variation at the neighborhood of those points. Furthermore, the Bonferroni simultaneous confidence intervals of the displacement of the key points can be constructed. Finally, dimensional deviation confidence interval of surface parts can be obtained.

3.2. Dimensional Deviation Estimation Method. According to combination theory, there are C_N^n possible sampling results if n samples are extracted from the population which consisted of N individuals. Obviously, there are C_N^n possible dimensional deviation confidence interval corresponding to the C_N^n sampling results. This means it is of huge randomness to estimate the surface dimensional deviation by sampling. However, along with the increase of sample size, $t_{\alpha/2ab}(1-n)$ in (14) will continue to decrease and $\sigma(p_{jk})_{sample}$ will converge to $\sigma(p_{jk})_{total}$ in probability. Therefore, the estimation error, $t_{\alpha/2ab}(1-n)(\sigma(p_{jk})_{sample}/\sqrt{n})$, decreases with the increase of sample size n. It indicates that a higher accuracy of dimensional deviation confidence interval can be obtained by increasing the sample size n. Hence, in order to reduce the sample size and improve the efficiency, a practical sampling method for dimensional deviation estimation of free-form surface parts is proposed. The specific steps of the proposed sampling are as follows.

Step 1. Randomly select two parts as samples and measure their dimensions.

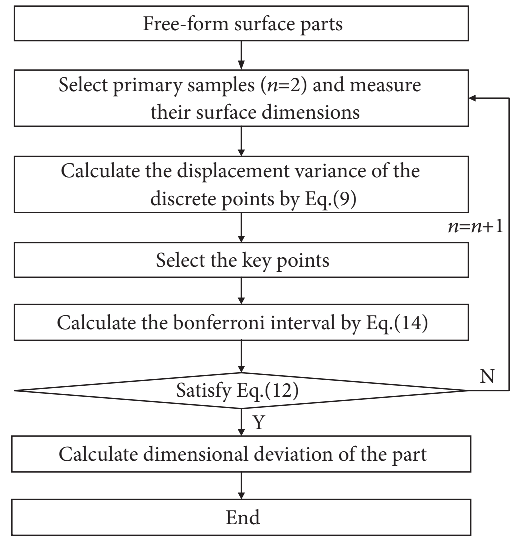


Figure 4: Flow diagram of the proposed methodology.

Step 2. Calculate the displacement variance of all of the discrete points, $\sigma^2(p_{jk})_{sample}$, $j = 1,\cdots,a$; $k = 1,\cdots,b$.

Step 3. Select the key points with local maximum displacement variance, p_l, $l = 1,2,\cdots m$.

Step 4. Calculate the estimation error of the displacement of the key points. If the estimation error is less than the given error limit for all of the key points, stop sampling. Surface dimension deviation can be accurately estimated by the samples. Otherwise, continue to select one parts as sample and proceed to Step 2.

After obtaining the optimal samples, dimensional deviation of the free-form surface parts can be easily calculated by comparing the difference between the average dimensions of the samples and the parts design dimensions. The flow diagram of the proposed methodology is shown in Figure 4.

4. Case Study

In this section, a set of random numbers that generated by Monte Carlo method are taken as the process parameters to simulate the effect of random noise on manufacturing process of free-form surface parts. Taking the deformed parts obtained by simulation as the object of study, the proposed method is analyzed and discussed.

4.1. Obtaining of Free-Form Surface Parts. A blade with complex surface with dimension of about 120 × 90 × 70 mm is chosen as an example as shown in Figure 5. The blade surface is lofted by the basic section curve along its stacking axis (Z axis). The basic section curve is composed of four parts: the leading edge, the tailing edge, the suction side, and the pressure side, as shown in Figure 6. Discrete points of the blade surface are shown in Figure 7. This blade has

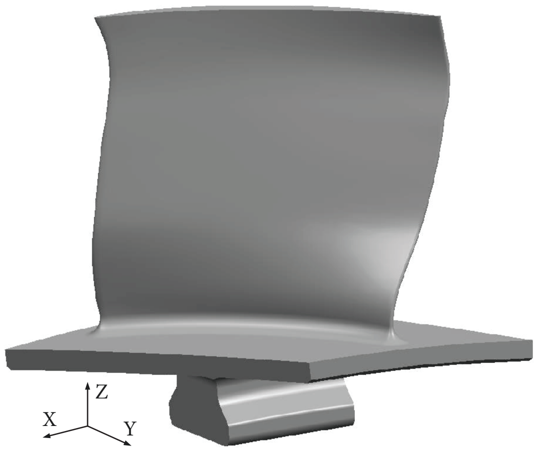


Figure 5: Blade CAD model.

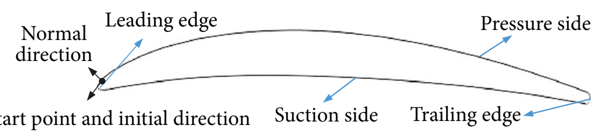


Figure 6: Structure of section curve.

Table 1: Process parameters and their values.

process parameter		value	distribution value
A:	Mold temperature/°C	80	$A \sim N(80, 3^2)$
B:	Melt temperature/°C	290	$B \sim N(290, 3^2)$
C:	Injection time/s	3	$C \sim N(3, 0.2^2)$
D:	Holding pressure/Mpa	25	$D \sim N(25, 2^2)$
E:	Holding time/s	15	$E \sim N(15, 1^2)$

the characteristics of uneven thickness distribution and steep curvature change.

The blade is fabricated by injection molding. Its material is glass fiber reinforced PA66 which is produced by BASF SE. The material trademark is A3WG3. There are two main factors, the mold and the process parameters, which affect the dimensional accuracy of blade. When the mold cavity is determined, the dimensional accuracy of the blade is mainly determined by the process parameters [33]. Hence, dimensional variation of injection molding parts is mainly caused by the variation of process parameters. Under the influence of random noise, the variation of process parameters can be regarded as approximately normal distribution [34]. The main parameters that affect the blade dimensions are selected to analysis as shown in column 1 of Table 1. Their setting values are shown in column 2 of Table 1. In order to simulate the influence of random noise on process parameters, the actual value of each process parameter is assumed to obey normal distribution as shown in column 3 of Table 1.

The blade finite element model including 46447 nodes and 246919 tetrahedron elements for blade injection molding is shown in Figure 8.

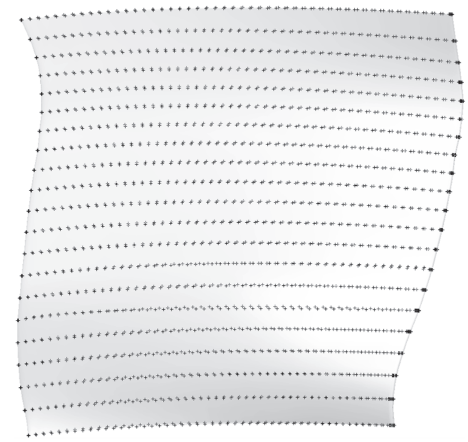


Figure 7: Discrete points on blade surface.

100 sets of process parameters which generated by Monte Carlo method are used as boundary conditions for blade injection molding simulation. Simulation result and blade dimensional deviation of the first set of parameters are shown in Figure 9. As can be seen from Figure 9, the blade deformation presents the characteristic of uneven distribution. The maximum deformation point is at the right corner of the blade tip, the maximum deformation is 1.136mm, and the minimum deformation in the middle part of the blade is 0.0658mm.

The starting point for calculating displacement is as shown in Figure 6, according to the order of starting point→leading edge→suction side→trailing edge→terminal point (starting point). Stipulating the deformation is positive while the angle between the displacement vectors of each point and the normal vector (as shown in Figure 6) at the starting point is less than 90 degrees. Otherwise the deformation is negative.

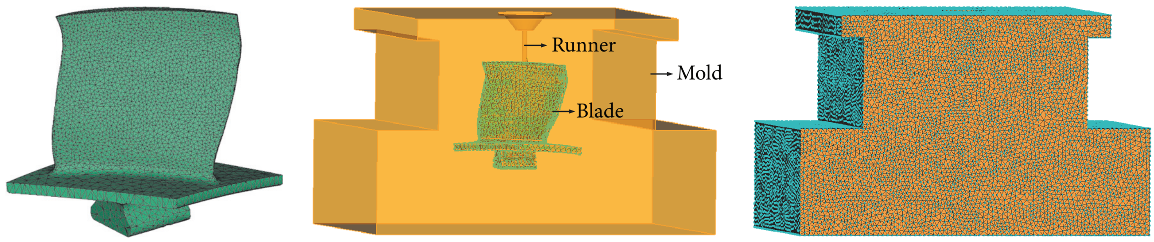
Deformation statistical histogram of point p_2 (as shown in Figure 11) is shown in Figure 10.

4.2. Dimension Deviation Estimation Results. According to the steps in Figure 4, displacement variance of all the discrete points is calculated and 4 key points are selected, as shown in Figure 11. When the tenth blade is selected, the estimation accuracy of dimensional deviation at all key points satisfies the given estimation error limit 0.05*mm*. The surface fitted by the displacement variance of the discrete points is shown in Figure 12.

Displacements estimation error (absolute value) of the four key points p_1, p_2, p_3, p_4 with the increase of sample is shown in Figure 13.

It can be seen in Figure 13, on the whole, displacements estimation error of key points decrease as the sample increase. What needs to be particularly pointed out here is this kind of decrease is overall trend.

Estimation error of blade dimensional deviation, using this 9 samples, is shown in Figure 14. It can be seen from Figure 14 that the estimation error is large at the leading and trailing edge, small at the suction side and pressure side. The



(a) Blade mesh model (b) Mold CAD model (c) Mold mesh model

Figure 8: The finite element model for blade injection molding.

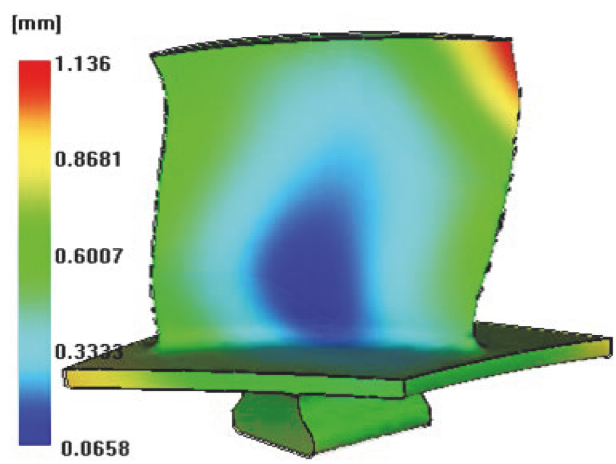


Figure 9: Blade deformation.

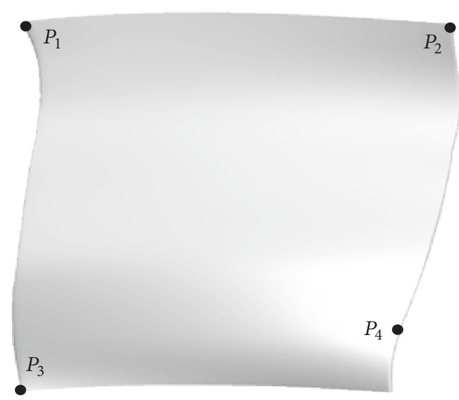


Figure 11: Maximum point of variance of deformation.

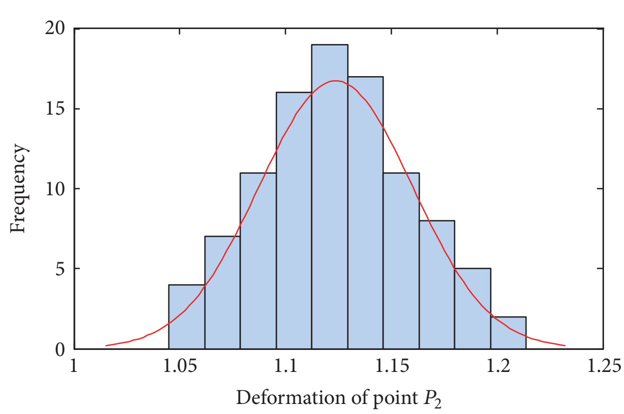


Figure 10: Statistical histogram of displacement at point P2.

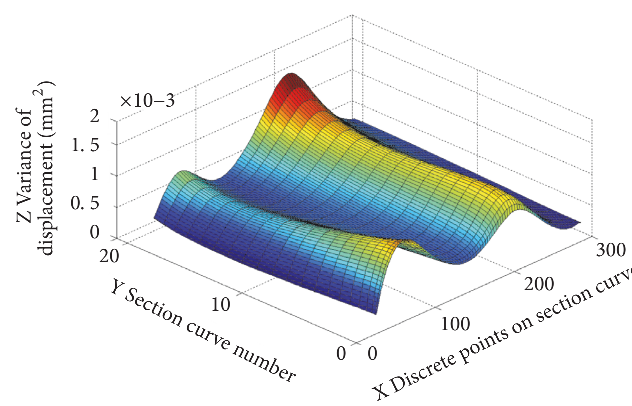


Figure 12: Surface fitted by blade variance of deformation.

maximum estimation error is not more than 0.05mm, which satisfies the given estimation error limit.

In order to further illustrate the effectiveness of the proposed algorithm, the sampling experiment is repeated 100 times in accordance with the steps in Figure 4. The sample size obtained from the 100 sampling experiments is shown in Figure 15. The maximum estimating error of the 100 sampling experiment is shown in Figure 16.

As can be seen in Figure 16, the sample size obtained from each sampling experiment will be different due to the uncertainty of sampling. When the estimation limit of dimensional deviation of the blade is 0.05*mm*, the required sample size is about 8-15, with an average of about 10. The estimation error satisfies the given confidence level requirement.

4.3. Comparison with Existing Algorithm and Discussion. In this study, displacements of the discrete points on free-form surface are employed to represent dimensional error; simultaneous confidence intervals of the discrete point displacements are employed to represent dimension deviation of the surface. These two measures are first presented. In order to demonstrate the necessity of doing these, an existing mean

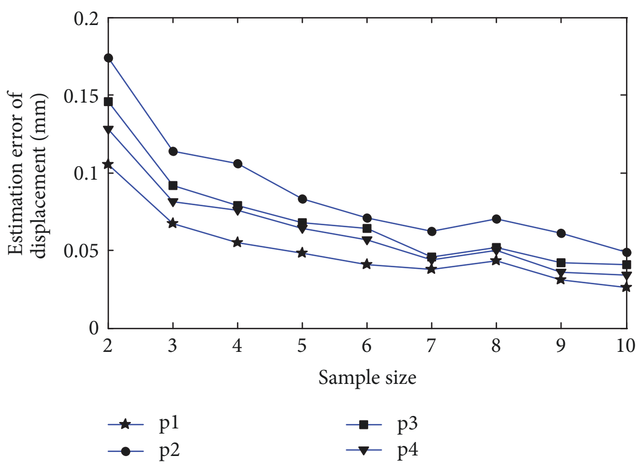


FIGURE 13: Displacements estimation error of the four points.

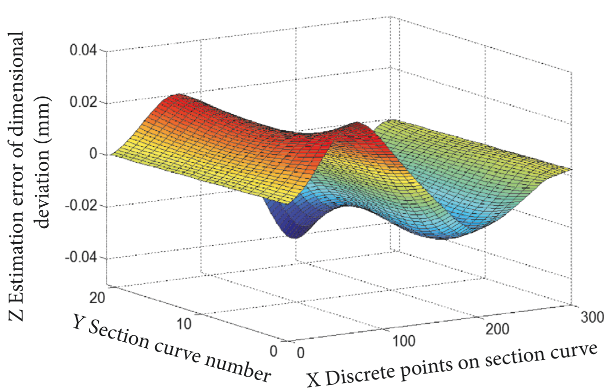


FIGURE 14: Estimation error of blade dimensional deviation.

value estimation method is adopted to estimate the blade dimension deviation in this section. Estimation results will be compared with the proposed method.

Equation (15) is often used for the mean value estimation in the case of unknown population variance [35]. It just meets the conditions of comparison.

$$\overline{y} - t_{\alpha/2}(n-1)\frac{s}{\sqrt{n}} \leq \overline{Y} \leq \overline{y} + t_{\alpha/2}(n-1)\frac{s}{\sqrt{n}} \quad (15)$$

with $\overline{y}$ as sample mean, $\overline{Y}$ as population mean, $t_{\alpha/2}(n-1)$ as quantile of t-distribution, s as sample standard deviation, and n as sample size.

Obviously, only one point's displacement can be estimated by (15). This means must using one point's displacement represent the whole surface deviation. Hence, p_2, the point with maximum displacement variance, is selected. Similarly, according to the steps in Figure 4, stop sampling while the displacement estimation error of p_2 is less than 0.05mm. Repeat the experiment 100 times. Sample size obtained from the 100 sampling experiments is shown in Figure 17. The required sample size is about 5-11, with the average about 6.

As can be seen in Figure 17, the sample size obtained from the comparative experiments is smaller than that of proposed method. However, the percentage of estimation error of the

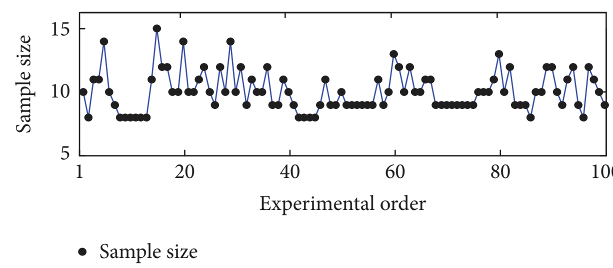


FIGURE 15: Sample size of 100 sampling experiments.

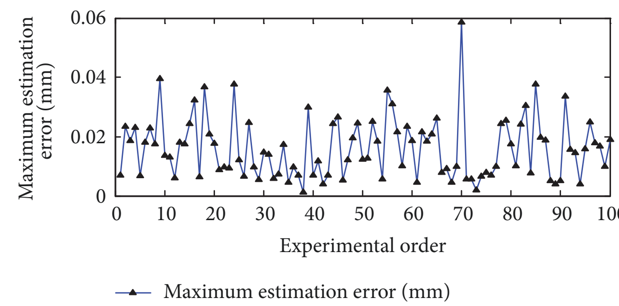


FIGURE 16: Maximum estimation error for 100 sampling experiments.

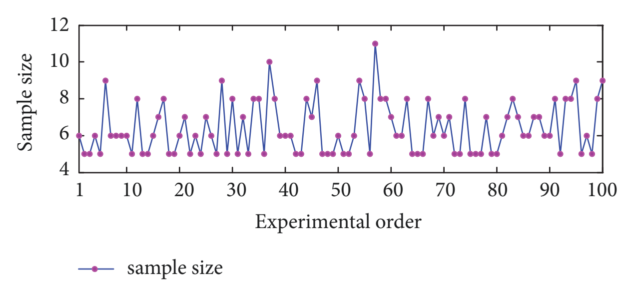


FIGURE 17: Sample size of 100 comparative experiments.

blade dimension deviation that less than 0.05mm of all the 100 times comparative experiments is 87%, far less than the confidence level of 95%. The pie charts in Figure 18 clearly show the estimated results of the two methods.

Displacements estimation error (absolute value) of the four key points p_1, p_2, p_3, p_4 with the increase of sample of one of the failed experiments is shown in Figure 19.

As can be seen in Figure 19, although the displacements estimation error of p_2 and p_3 meet the requirement, p_1 and p_4 cannot. This is because the sampling process ignores all points except p_2. The results of comparative experiments confirm the superiority of the proposed method on the accuracy and confidence level of dimension deviation estimation for free-form surface parts.

5. Conclusions

Aiming to estimate the dimensional deviation of free-form surface parts, a practical method is proposed in this paper. The main conclusions of this study are as follows:

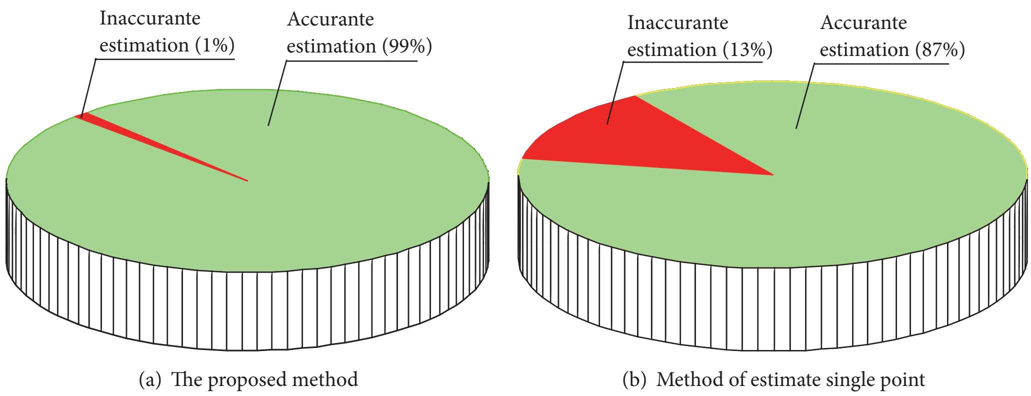


FIGURE 18: Comparison of the estimated results of two methods.

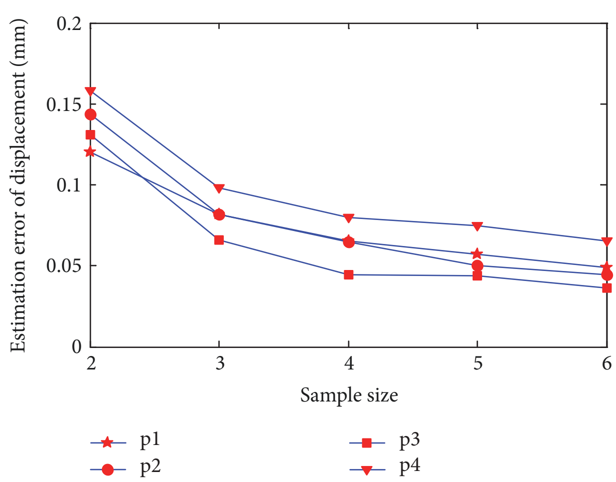


FIGURE 19: Displacements estimation error of the four points of the failed experiment.

(1) Displacements of the discrete points on free-form surface are employed to represent dimensional error. Estimating parts' dimensional deviation is actually to estimate the simultaneous confidence intervals of the discrete point displacements.

(2) Points with local maximum displacement variance are regarded as the key points and used to reflect free-form surface dimensional variation at the neighborhood of those points. Furthermore, Bonferroni simultaneous confidence intervals of the key points are used to estimate the confidence interval of the dimensional deviation of free-form surface parts. By increasing samples, the estimation accuracy can be improved. As a whole, displacements estimation error of key points decrease as the sample increase.

(3) The proposed method and an classical mean value estimating algorithm are employed to estimate the dimensional deviation of a blade. The percentage of estimation error of the blade dimensional deviation that is less than 0.05mm, which is the estimation error limit, of all the 100 times sampling experiments is 99%, exceeding the given confidence level of 95%, while the percentage of the existing method is below the confidence level, only 87%. Sampling experiments indicated that estimating dimension deviation of free-form surface parts with the inspection information of a single point will lead to unacceptable estimation error. In contrast, the proposed method has high estimation accuracy and confidence.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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