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A dataset of measured machining deviations of compressor rotor blades

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Abstract: The uncertainty in blade machining deviations leads to the offset in the average performance and the performance scatter of aero-engine compressors, posing a threat to the safe operation of engines. Therefore, quantifying the uncertainty effects of machining deviations is critically important. However, due to factors such as prolonged inspection cycles and high costs, geometric data on blade machining deviations remain scarce. Most uncertainty quantification analyses are conducted under assumed statistical distributions of deviations, making it difficult to guarantee the accuracy of the quantification. In this paper, a dataset of measured machining deviations of 100 compressor rotor blades is presented. And it includes 7 types of machining deviations of 13 blade sections from blade root to tip. The work fills a critical gap in available geometric deviation data for compressor rotor blades, and provides a reliable foundation for subsequent uncertainty quantification investigation.

Background & Summary

With the increasingly demanding target for thrust-to-weight ratio and lightweight of modern aero-engines, the aerodynamic loading of the compressor continues to increase. The blade is the basic unit of the compressor, so the aerodynamic performance of the compressor depends heavily on the blade geometry. Therefore, the machining quality of aero-engine compressor blade profiles is subject to stringent requirements [1]. In recent years, machining capabilities have been significantly enhanced through the introduction of innovative technologies such as machining deviation compensation and tool path and orientation optimization [2,3]. However, constrained by factors such as the complex geometric of blades and the low machinability of materials, machining deviations remain inevitable. As a result, the actual geometry of compressor blades consistently deviates from the design specifications [4-6]. The complex internal flow in the compressor, particularly under off-design conditions [7], will amplify the influence of the blade machining deviations on the aerodynamic performance [8]. For example, the structure and position of the shock wave and even stability margin are sensitive to the machining deviation of the blade stagger angle [9,10]. For the compressor blades machined in batches, the machining deviations have typical uncertain characteristics because of cutting forces, vibrations and other factors. These machining uncertainties have become the main reason for the excessive scatter of the compressor's service performance [11-13]. Therefore, understanding the impact of the blade machining deviations is critical for the robust design and performance improvement of the compressor [14-16].

At present, the most common uncertainty quantification (UQ) methods in the field of turbomachinery are based on the probability schemes, such as Monte Carlo method [17,18], polynomial chaos method [19,20] and adjoint method [21,22]. The first step in the implementation of these UQ methods is to establish a probability distribution model that can reflect the uncertainty characteristics of the blade machining deviations. In fact, the UQ of the blade machining deviations can be regarded as the propagation problem of the random input in the complex nonlinear system. Obviously, the input probability distribution model has an important influence on the final UQ results of the aerodynamic performance of the compressor blade. It is noteworthy that the establishment of a reasonable and accurate probability distribution model depends on the deep understanding and statistical analysis of the actual measured data of the machining deviations.

The classical Gaussian distribution (symmetrical bell-shaped curve) is the most commonly used probability density function (PDF) model in engineering applications. Thus, it is also the default PDF model for quantifying the uncertainty of blade machining deviation in the early stage. Garzon et al. [23] obtained the profile detection data of 150 compressor rotor blades, but they habitually believed that the machining deviations obeyed the Gaussian distribution without the statistical analysis of the measured data in the UQ analysis. Similarly, Lamb [24] and Duffner [25] also assumed that the machining deviations of the compressor and turbine blades followed the standard Gaussian distribution when studying the uncertain impacts on the aerodynamic performance. Wang et al. [26] used the Gaussian distribution model to describe the uncertain characteristics of the stagger angle and leading-edge radius of compressor blades. Ma et al. [27] used 2 statistical test methods (i.e., Q-Q diagram and Shapiro-Wilk) to reveal that the leading-edge deviation of a high subsonic compressor blade obeyed the Gaussian distribution. Obviously, the Gaussian distribution model has become the mainstream probability model used for UQ of the machining deviations in the field of turbomachinery.

Although the Gaussian distribution is the most commonly used distribution, there are some open literatures show that the machining deviations don't necessarily satisfy the Gaussian distribution. Lange et al. [28] found that the maximum camber deviation of the Rolls-Royce engine blades fitted the Weibull distribution. Subsequently, they found that the profile deviation of the compressor blades presented the feature of 'bimodal' distribution, rather than the standard Gaussian distribution (unimodal distribution) [29]. According to the statistical analysis of 1082 centrifugal compressor blades by Panizza et al. [30], the thickness deviation distribution at the hub shows obvious 'skewed' characteristics, which is different from the symmetry of the Gaussian distribution. Liu et al. [31] measured the machining deviations of the leading/trailing edge radius, stagger angle, and other parameters of 100 rotor blades of a high-pressure compressor. In the process of statistical modeling, the machining deviation parameters are modeled by the Gaussian distribution, but it should be noted that the probability shapes of some measurement data deviate from the distribution characteristic of the Gaussian model.

The above studies are helpful to understand the real statistical law of the machining deviations of the compressor blades. In addition, some studies have shown that the input PDF model based on measured data is very important for the UQ analysis of the machining deviations on the aerodynamic performance of the compressor blades [8,10]. Furthermore, we should realize that the profile measurement of the compressor blades has the following characteristics: 1) The detection cycle is long and the cost is high; 2) To save costs, the sampling inspection method is often used in engineering to obtain measured data; 3) The compressor blade geometry involves data information security and other restrictions. Based on the above reasons, many studies in the current stage are extremely difficult to obtain sufficient measured data. Due to the lack of underlying data support, researchers have to use a subjectively assumed probability model for UQ analysis [32,33]. In the case of missing or incomplete information, PDF models based on subjective experience are likely to introduce unpredictable quantitative error risks, which seriously threaten the reliability of UQ analysis [34,35]. Additionally, the three-dimensional (3D) structure of the compressor blade is complex, the thickness from the blade root to the blade tip is uneven with different machining difficulty, which will inevitably lead to the difference in the probability distribution characteristics for the blade sections. The conclusion of Reference 36 points out that it is of great significance to extract the measured data of the machining deviations and carry out relevant statistical analysis for accurately establishing a reasonable probability model and ensuring the credibility of UQ results.

In the open literatures, there is no measured machining deviation data for the 3D compressor rotor blades. In this paper, a dataset of measured machining deviations of 100 compressor rotor blades is presented, including 7 types of machining deviations of 13 blade sections from blade root to tip. And it has been hosted on website (https://doi.org/10.57760/sciencedb.27122 [37]). The work provides an important reference for further understanding the statistical characteristics of the machining deviations of the compressor blades, and provide a solid underlying data support for the subsequent research on UQ.

Methods

1. Types of blade machining deviations

A 3D compressor rotor blade is our research object, which is machined by the 5-axis computer numerical control (CNC) machine. Its primary material is titanium alloy, which offers high load-bearing capacity, excellent fatigue strength and fracture toughness, making it well-suited for the complex operating environment of

aero-engines. However, the inherent difficulty in machining the material is one of the main reasons why machining deviations are inevitable. In engineering, Considering the inspection cost, the method of 'sampling inspection' is adopted in the inspection of the compressor blade profile, resulting in limited sample size. In addition, it is worth explaining that in the previous research on 'data-driven UQ method based on precondition matrix' [38], it is found that the sampling amount of the machining deviations reaches more than 40, which satisfies the minimum requirement of UQ. At our present work, the measurement samples include 100 rotor blades, whose 13 equidistant sections' (H_i, i=1, 2, …, 13) coordinates from the root to the tip of the blade are measured by the coordinate measuring machine (CMM). The definitions of the measured sections and blade geometry parameters are shown in Fig. 1 and Fig. 2, respectively.

CMM can directly obtain the 3D point cloud data of the blade geometry. The machining deviation obtained by comparing to the design geometry is the comprehensive deviation. However, considering that the subdivided tolerances are shown in the blade drawing, to determine whether the blade is qualified, the comprehensive deviation needs to be decomposed [39]. Firstly, carry out translation and rotation of the blade profile, so that the actual and the design basically coincide, and further obtain the position deviations, such as the deviation of the stagger angle. And then, by calculating the normal distance between the discrete point of the blade profile after translation and rotation and the design, the blade profile deviation can be obtained, which has the characteristic of the high dimensional randomness. It is worth explaining that after mastering the statistical distribution characteristics of the blade profile deviation, the NURBS (Non-Uniform Rational B-Spline) combined K-L (Karhunen-Loève) expansion method was used to realize the blade random profile modeling in the earlier work [14,40]. Additionally, the leading/trailing-edge radius and maximum thickness are the important design parameters for the airfoil. In engineering, three types of the machining deviations need to be extracted to assist inspection personnel in making judgements on 'leaving and discarding' the blade. Referring to the method of 'parameterization of airfoil' in the Reference 39, based on the iterative calculation of actual airfoil discrete points to obtain the mean line, the actual leading/trailing-edge radius and maximum thickness can be obtained, and corresponding deviations can be proposed compared with the design values. The machining deviation types of the compressor rotor blades measured are shown in Table 1. At the same time, Table 1 shows the machining tolerances for the compressor rotor blade, and among them, e_{PP} and e_{SP} represent that the maximum minus the minimum of the machining deviations of the pressure and suction profiles, respectively.

Fig. 1 goes here.	Fig. 2 goes here.

Table 1 Types of blade machining deviation.

Type	Sign	Machining tolerance
Leading-edge radius/mm	ΔR_{LE}	[-0.13, 0.13]
Trailing-edge radius/mm	ΔR_{TE}	[-0.13, 0.13]
Maximum thickness/mm	ΔR_{Max}	[-0.2, 0.2]
Chord length/mm	Δc	[-0.3, 0.3]
Pressure profile/mm	e_{PP}	[0, 0.2]
Suction profile/mm	e_{SP}	[0, 0.2]
Stagger angle/º	$\Delta\theta$	[-0.5, 0.5]

2. Statistical analysis method

Fig. 3 shows the procedure of UQ. From it, as the input of UQ system, the influence of the statistical distri-

butions of the variable X on the quantification response Y is self-evident. Referring to the References 41 and 42, it is worth explaining that when different statistical distributions are used to fit for the same set of the deviation data and as the input of the UQ system, the UQ response' difference of the compressor aerodynamic performance is significant, especially in the performance scatter. Therefore, it is necessary to carry out UQ based on the statistical characteristics of the data of the measured machining deviations, which also reflects the importance of underlying data analysis. To fill a key gap in the statistical analysis of the machining deviations of the compressor rotor blades, a variety of statistical parameters are used for data mining. For a set of measured data $x = [x_1, x_2, x_3, ..., x_k, ..., x_n]$, the following statistical parameters are defined.

Fig. 3 goes here.

1) Machining systematic deviation μ:

$$\mu = \frac{1}{n} \sum_{k=1}^{n} x_k \tag{1}$$

Here, μ is used to represent the overall situation of the machining deviation of the compressor blades. k is the sample serial number, and the total sample number is $n=100$.

2) Scatter of the machining deviation σ:

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{k=1}^{n} (x_k - \mu)^2} \tag{2}$$

Here, σ is used to characterize the inconsistency of the blade machining deviation.

3) Skewness of the machining deviation Sk:

$$Sk = \frac{1}{n-1} \sum_{k=1}^{n} (x_k - \mu)^3 / \sigma^3 \tag{3}$$

When the blade machining deviation is symmetrically distributed, the skewness $Sk=0$. When the measured data on the left side of the mean value μ is less than that on the right side, it represents a left skewed distribution, that is, the skewness $Sk<0$; Conversely, the skewness $Sk>0$, as shown in Fig. 4.

4) Extreme relative machining deviation δ:

$$\delta = x_{\text{Extre}} / y_{\text{Design}} \tag{4}$$

Where x_{Extre} is the extreme deviation of the blade and y_{Design} is the design value of the blade geometry parameter.

5) The boxplot is used to characteristic mining for the measured data of the blade machining deviation. Fig. 5 presents the parameter definition of the boxplot. The range of the box (blue area) represents the upper quartile (Q1) and the lower quartile (Q2) of the measured data. The solid line in the box represents the median value. In addition, the black point represents the mean value, and the grey points represent the outliers of the blade machining deviations.

Fig. 4 goes here.
Fig. 5 goes here.

Data Records

The dataset is available at https://doi.org/10.57760/sciencedb.27122 [37]. The machining deviation data of 100

aero-engine compressor rotor blades, with each blade comprising 13 measured sections and 7 types of machining deviations, totaling 9, 100 data values, are published on the Science Data Bank (SciDB). It includes the deviations in the following order: leading-edge radius (ΔR_{LE}), trailing-edge radius (ΔR_{TE}), maximum thickness (ΔR_{Max}), chord length (Δc), pressure profile (e_{PP}), suction profile (e_{SP}), and stagger angle ($\Delta\theta$).

This sequence corresponds exactly to the order of sub-tables presented in the summary table named 'Measured machining deviation data of aero-engine compressor blades.' Subsequently, each row in the sub-tables represents the machining deviations of 1~13 blade-height sections of a single blade sample, while each column corresponds to the machining deviations of 1~100 blade samples at a specific blade-height section, and the data recording schematic diagram is shown in Fig. 6.

Fig. 6 goes here.

Data Overview

As described in Section 2, a comprehensive understanding of the statistical characteristics of machining deviations is a prerequisite for conducting UQ analysis. Therefore, this section provides a concise summary. First, based on items 1), 2), and 4) in Section 2, the spatial distribution characteristics of machining deviations along the blade height is analyzed and summarized in Table 2. Additionally, to further analyze the probabilistic statistical distribution characteristics of machining deviations at different measurement sections, 5 blade sections (equidistant sections from root to tip, including H_1, H_4, H_7, H_{10} and H_{13}) are selected. Based on items 3) and 5) in Section 2, the results are summarized in Table 3.

Table 2 Spatial distribution characteristics of machining deviations along the blade height.

Type	Systematic deviation	Scatter	Relative deviation/Extreme value	Machining difficulty
ΔR_{LE}	Significant, transitioning from thin to thick state along the blade height	Increasing along the blade height	-12%~12%	Increasing along the blade height
ΔR_{TE}	Significant near the root and tip regions	Decreasing first and then increasing gradually along the blade height	-12%~12%	More difficult to machine of the root and tip
ΔR_{Max}	Significant, transitioning from thin to thick state along the blade height	More scattering near the blade root and tip	-3%~6.5%	More difficult to machine of the root and tip
Δc	Not significant	Almost identical except for the blade root section	-0.63%~0.45%	Low machining difficulty
e_{PP}	Significant	No obvious variation law along the blade height	--	--
e_{SP}	Significant near the tip regions	No obvious variation law along the blade height	--	--
$\Delta\theta$	Significant, showing an overall 'under-deflection' state	Increasing linearly and then stabilizing along the blade height	-0.45º~0.35º	Gradually increasing and then stabilizing along the blade height

Table 3 Probabilistic statistical distribution characteristics of machining deviations.

Type	Law of probability distribution	Condition of lack of data	Condition of machining deviation outliers

ΔR_{LE}	Don't have the 'Gaussian distribution' characteristic in multiple sections	H_1, H_{10} and H_{13}	Expect H_7
ΔR_{TE}	Approximate 'Gaussian distribution' in most sections	H_4	H_1
ΔR_{Max}	'Skewed' and 'bimodal' distribution characteristics	H_1 and H_7	Expect H_4
Δc	Significantly deviate from the 'Gaussian distribution'	H_{10}	All sections
e_{PP}	'Gaussian', 'right skewed' and 'multi-modal' distributions are present simultaneously	No appearing	No appearing
e_{SP}	Deviate from the 'Gaussian distribution' in most sections	H_1 and H_7	H_1
$\Delta\theta$	Deviate significantly from 'Gaussian distribution' except for H_7 and H_{10}	No appearing	Expect H_1

Technical Validation

To validate the usability of the machining deviation dataset, frequency histograms of 7 types of machining deviations at the blade root region (H_1) are first presented, as shown in Fig. 7. It can be observed that the distributions of all types of machining deviations are concentrated and fall within the tolerance ranges provided in Table 1. This indicates that the blade machining and measurement processes are well-controlled, thereby demonstrating the reliability of the data.

Furthermore, whether the sample size is sufficient is also crucial for conducting UQ. For this purpose, taking stagger angle deviations at the blade tip region (H_{13}) as an example, we perform random sampling with an incremental increase of 10 in sample size per iteration. The mean and standard deviation of the samples are calculated according to Equations (1) and (2), and the results are shown in Fig. 8. It can be observed that when the sample size reaches 40, the variations in both statistical parameters with increasing sample size essentially stabilize. Meanwhile, in the study of compressor cascades reported in Reference 38, which investigated the convergence of aerodynamic UQ results with respect to the sample size of stagger angle deviations, the critical sample size was also found to be 40, consistent with the above. Therefore, the dataset provided is capable of supporting the execution of UQ studies.

Fig. 7 goes here.
Fig. 8 goes here.

Data Availability

The data can be accessed at https://doi.org/10.57760/sciencedb.27122.

Code Availability

No custom code is generated for this research. The measurement and analysis procedures comply with the corresponding manual, and the statistical methods employed are conventional.

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Author contributions

Limin Gao and Yue Dan contributed to data collection and processing. Haohao Wang contributed to the data analyzing. Ruiyu Li and Guang Yang reviewed the statements of data records. All authors have read and approved the final manuscript.

Competing information

The authors declare no competing interests.

Figure legends
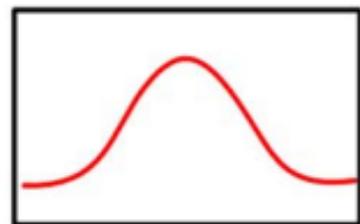
Fig. 1	Diagram of equidistant sections.
Fig. 2	Blade geometry parameters.
Fig. 3	Procedure of UQ.
Fig. 4	Distribution schematic diagrams. (a) $Sk<0$, (b) $Sk>0$, (c) $Sk=0$.
Fig. 5	Definition of boxplot.
Fig. 6	Data recording schematic diagram.
Fig. 7	Frequency Histograms of 7 types of machining deviations at H_1. (a) ΔR_{LE}, (b) ΔR_{TE}, (c) ΔR_{Max}, (d) Δc, (e) e_{PP}, (f) e_{SP}, (g) $\Delta\theta$.
Fig. 8	Statistical analysis of stagger angle deviations at H_{13}.

Tip: H_{13}

Equidistant
Section: H_i

Hub: H_1

X

Z

Profile deviation: e

Mean line

Maximum thickness: R_{Max}

Inscribed circle

Leading-edge radius: R_{LE}

Trailing-edge radius: R_{TE}

Chord line: c

Y

Stagger angle: θ

Z
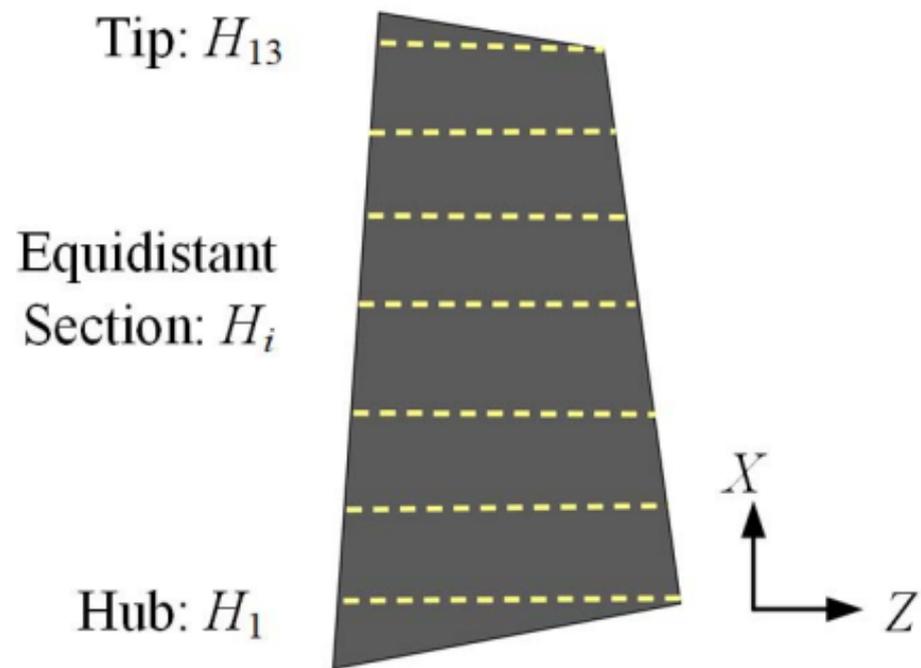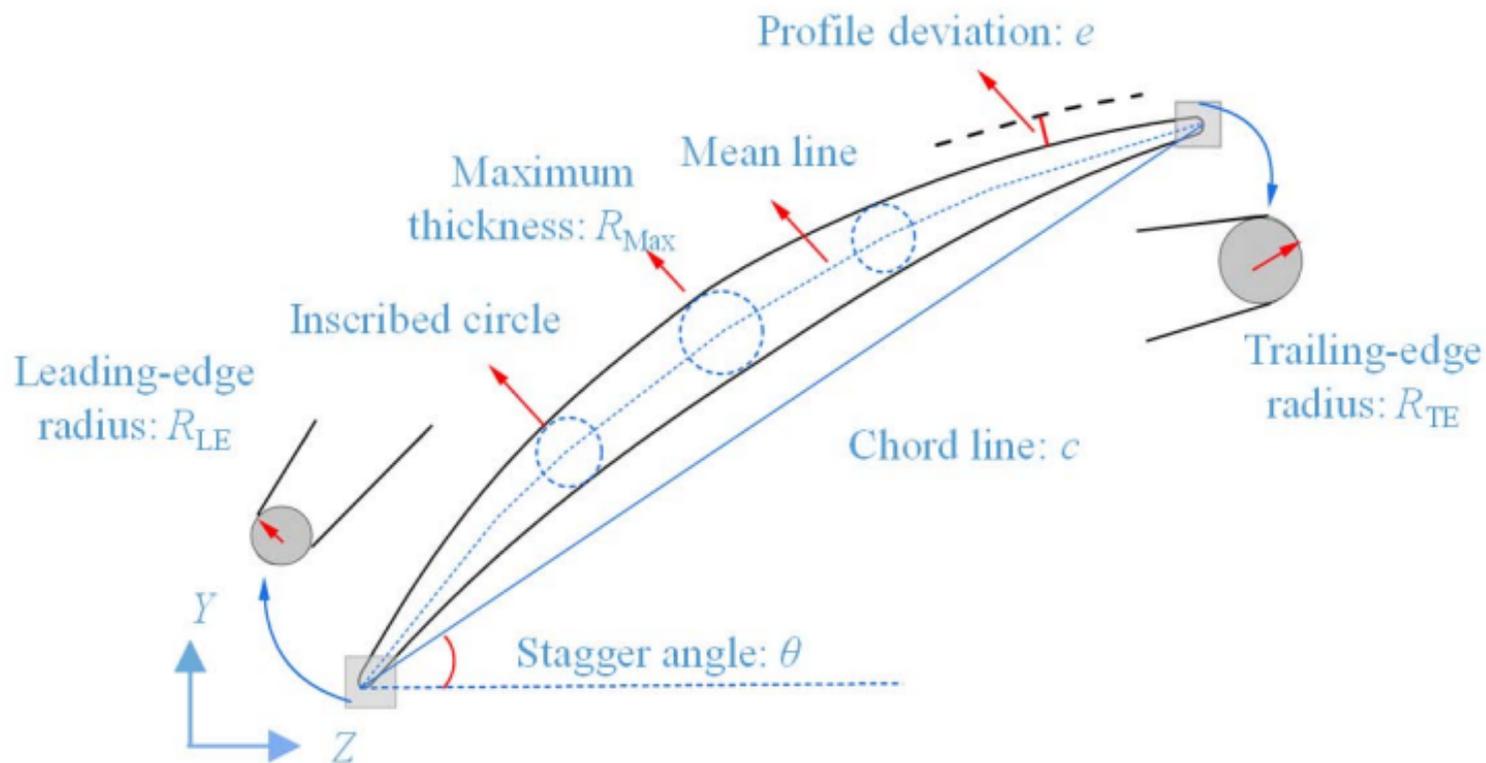
Random variable X
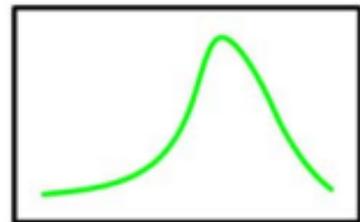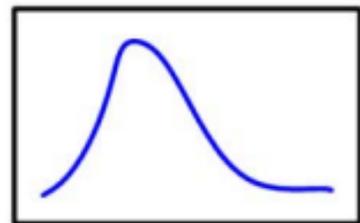
Uncertainty propagation

System

Random response Y

Scatter

Mean

(a)　　　　　　　　(b)　　　　　　　(c)

Box
Median
Mean
Outlier
IQR
Q2-1.5IQR   Q2   Q1   Q1+1.5IQR

Measured machining deviation data of aero-engine compressor blades.xlsx

(a) (b) (c) (d) (e) (f) (g)

Sample size gradually increasing

Sampling with different sizes
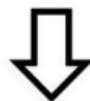
Variations in statistical parameters with increasing sample size