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Original Research Article

Use Recognizable Digital twin in Virtual Measurement for General Both Evaluation of Additive & Subtractive Manufacturing Process

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ABSTRACT

Background: "Subtractive manufacturing" and "additive manufacturing" are inseparable mechanical processing manufacturing processes, and must be carried out at the same time is an established processing concept. In order to achieve continuous improvement, production machine tools are required to effectively identify the causes of possible defects. Therefore, the uncertainty of performance prediction is a very important subject.

Methods: Combination of Digital Twin 、RPE and VM is used to make the quantized value close to the true overall average value, which can be used with other algorithm theorems.

Results: Final Total σ (sigma) represents the σ control value after comparing the DT value of these types of "reduced additive manufacturing" with the experimental value of ET. It shows result of overall additive manufacturing is 53 σ , and Table 5 shows that of overall subtractive manufacturing is 64 σ . It can be evaluate the performance of the concept of adding or subtracting material manufacturing and processing to promote the subsequent development of artificial intelligence (AI).

Conclusions: The combined RPE method is not limited to cutting test parts of any geometry, and can be designed that the cutting test parts also collect sufficient statistical data. The detailed information about machine tool analysis considers the advantages and disadvantages of each machine tool. Designers must continue to improve the performance of adding and subtracting materials, and objectively give evaluation qualified performance indicators, in order to continuously correct the improvement and perform performance evaluation.

Keywords: Multi-type machine tool, Subtractive manufacturing, Additive manufacturing, RPE, Recognizable Performance Evaluation, Recognizable Virtual Measurement, Digital Twin

INTRODUCTION

"Subtractive manufacturing" is an important part of the traditional precision machining industry, and one of the more representative ones is the processing and manufacturing of multi-axis machine tools. "Additive manufacturing" is a new low-volume manufacturing and processing method in the past 30 years. Its representative advantage is that it does not need to deliberately make molds, as long as it can be processed directly, but the processing time is longer and can be processed immediately. The number of workpieces is also relatively limited. However, as the requirements for accuracy continue to increase, these two manufacturing and processing methods are usually rarely confused. Some documents even directly state: "These are two completely different manufacturing methods. It is impossible to use the same evaluation method to evaluate performance. Evaluated". However, based on practical considerations, these two manufacturing and processing methods must often be carried out simultaneously or interactively, which often causes a major problem in industrial processing.

The necessity of "subtractive manufacturing" and "additive manufacturing" at the same time is certain, and such interlaced processing seems to have become a trend. However, how to continuously improve processing in a reasonable way? Qualified performance improvement must be evaluated objectively, and continuous revision and improvement must be made based on identifiable and quantifiable performance evaluations. Effectively identify the reasons for possible defects to make continuous improvement possible, which makes the uncertainty of performance prediction an important issue.

LITERATURE REVIEW

When considering whether a part is manufactured with additive or subtractive materials, the complexity is generally considered. For high-complexity parts, additive manufacturing is an inevitable choice, because it can give complete geometric freedom to build parts with complex internal structures and functions. Subtractive manufacturing based on CNC machining can achieve high production efficiency and very tight tolerances for parts with conventional shapes. Therefore, the more complex parts are, the more suitable the additive manufacturing technology is. It should be noted that if the part specifications require stricter tolerances, traditional methods are usually required.

However, these two methods have their own advantages and limitations. Laser sintering additive manufacturing essentially uses a laser beam to melt expensive powder along the tool path, creating only one layer of a part at a time. This process is at least an order of magnitude slower than traditional CNC metal processing. To achieve the speed of subtractive manufacturing, it is necessary to weigh the thickness of each layer in three dimensions. You can use higher energy input or generate a thicker powder layer or faster molding to increase productivity, but the surface finish will be affected. Or you can accept a slow process to form smaller layers and get a better surface finish. It is even possible to accept a slower process to form a thinner layer to obtain a better surface finish. In some types of CNC machine platforms, you still need a post-deposition process. This is where the "struggle" between additive manufacturing and subtractive manufacturing lies. These two technologies are regarded as competing technologies, rather than complementary to each other. Here we seek the possibility of hybrid manufacturing between them.

There are many different processing methods for "subtractive manufacturing",

but going to about precision and ease of implementation, multi-axis machine tools will be the first choice. In 2020, Cheng Chen Xi Wang Yan Wang Dandan Yang Fangyi Yao Wenxiong Zhang Bo Wang Galhenage Asha Sewvandi Desuo Yang Dengwei Hu [1], In subtractive manufacturing, a piece is processed from the digital design to get the final 3D model and residual material, but in additive manufacturing the required amount of material is deposited layer by layer. From this, it can be seen that there are benefits to doing both "subtractive manufacturing" and "additive manufacturing". In 2019, David Gräfe, Sarah L. Walden, James Blinco, Martin Wegener, Eva Blasco and Christopher Barner-Kowollik [2], Due to the inherent nature of the manufacturing process, 3D printed structures require excess material to structurally support complex features. And this support material must be removed after printing, sometimes as part of subtractive manufacturing.

Another reason that makes additive manufacturing and subtractive manufacturing difficult to assess together is the processing quality, especially the surface roughness. Because at this stage, the surface roughness level of additive manufacturing is far from that of subtractive manufacturing (multi-axis machine tools).

But Multi-process hybrid production technology can provide a comprehensive choice from pure additive to subtractive manufacturing. Multi-process mixed processing is the "bridge". Combining the two technologies with printing materials, adding metal to known parts, building parts from scratch, and then fusing them together. In most cases, additively manufactured components cannot meet the needs of traditional processing. Some functions require surface finish or tolerances, which cannot be achieved by direct material deposition.

In 2021, Franco Concli, Luca Bonaiti, Riccardo Gerosa, Luca Cortese, Filippo Nalli, Francesco Rosa and Carlo Gorla [3], Additive manufacturing can design the possibility of adding materials and explore optimized solutions for critical parts through the bending fatigue behavior of production. In 2021, Volker Böß, Berend Denkena, Marc-André Dittrich, Talash Malek and Sven Friebe [4], mentioned Additive manufacturing is indeed a flexible alternative to traditional manufacturing processes. However, manufacturing costs increase when the optimal process parameters for custom products or small batches need to be determined experimentally. Simulations are therefore required to reduce the effort required for experimental testing. Dixel-based simulation allows modeling of additive manufacturing of different geometries by considering multi-axis machine kinematics and local process conditions. In 2021, Xiaoping Liu, Kuaishe Wang, Ping Hu, Xiaomei He, Baicheng Yan and Xuzhao Zhao [5], SLM is a typical additive manufacturing technology used to prepare parts with complex cavity geometry and high surface precision. In recent years, additive manufacturing technology has become a research hotspot in the manufacture of refractory and refractory metals. In 2021, Maite Aretxabaleta, Alexander B. Xepapadeas, Christian F. Poets, Bernd Koos and Sebastian Spintzyk [6], Evaluate CAD/CAM technologies and materials for implementation into production workflows, depending on the Factor of Safety (SF) each material provides due to different technologies and materials to manufacture.

Through a precision five-axis machine tool, supplemented by a laser melting (SLM) deposition nozzle, parts are printed from scratch, and the nozzle is used as a tool changer, which is the same as a conventional milling tool to support multiple nozzles and different powders.

This is a very serious problem: because there are several special industries that will meet the needs of the application, and must choose and choose between metal and non-ferrous metal products, the most common ones are "oral medical reconstruction" and "navigation components" Lightweight. Therefore, different processing materials should be able to be compared with each other in order to keep up with the diversified and changing needs of modern industries. For examples In 2020, Taiseer A. Sulaiman [7], Referring to patient-friendly technologies and services in the manufacture of dental restorations and appliances using a variety of materials such as wax, metal, composite resins and ceramics, the structural properties of these materials compared to restorations prepared by traditional and additive manufacturing methods will vary. SLM laser printing in additive manufacturing is now in full bloom, but there are still many force majeure experimental processes that need to be improved. Perhaps, it can also be said that SLM laser printing is not very mature in many parts. For examples, In 2021, Roberto Paoli, Davide Di Giuseppe, Maider Badiola-Mateos, Eugenio Martinelli, Maria Jose Lopez-Martinez and Josep Samitier [8], Digital manufacturing (DM) and rapid prototyping (RP) for microfluidic applications are other limiting scenarios for manufacturing technologies. Mainly used for different materials and bonding strategy limitations.

In 2021, S.L. Sing, S. Huang, G.D. Goh, G.L. Goh, C.F. Tey, J.H.K. Tan and W.Y. Yeong [9], Adoption in the industry is still limited, and one of the main barriers identified is the lack of materials that can truly directly use L-PBF to make functional parts. A comprehensive overview of the underlying scientific themes behind them, including key contributing factors and trends, sheds light on deficiencies.

In addition, the reason why additive manufacturing and subtractive

manufacturing are not easy to be evaluated together is the non-traditional processing process. Take today's processing as an example. The so-called non-traditional processing refers to: In additive manufacturing, it is not performed by multi-axis machine tools, and SLM laser 3D printing is not the main method in subtractive manufacturing. Unconventional processing techniques are different from conventional processing techniques because they use alternative types of energy (such as thermal energy, electrical energy, and chemical energy) to form or remove materials. In 2021 · Julian Nold, Christian Wesemann, Laura Rieg, Lara Binder, Siegbert Witkowski, Benedikt Christopher Spies and Ralf Joachim Kohal [10] Unconventional machining processes can replace the original types of energy, such as thermal, electrical and chemical energy to form or remove material, and the fracture resistance of ISO-compliant specimens is used in additive manufacturing.

In 2017 · Zhen-Hua Wang, Dian-Yao Gong, Xu Li, Guang-Tao Li and Dian-Hua Zhang [11] Mean absolute error, mean absolute percentage error, and root mean square error were established, and these relevant correlation coefficients were all suitable for evaluating the performance of the model. In their work, predictions were compared with measurements to verify the accuracy of prediction models. In 2017 ·

Sina Seifi 和 Mohammad Saber Fallah Nezhad [12] Selection of the correct process capability indicators and their sampling distribution is critical. Statistical techniques can be used to obtain sample distributions. A variable sampling plan was developed based on the resubmitted batches using the Process Capability Index. In the proposed sampling plan, batches are inspected multiple times based on quality levels. model. In 2019, Mi Xiao, Yongsheng Yi, Jinhao Zhang, and Wei Li [13] communicated that in complex

engineering systems, different metamodels can be constructed through using different component modeling techniques. The best metamodel for quantifying this uncertainty and incorporating it into the metamodel selection introduces the Bayes' theorem along with an additive adjustment factor. From 2016 to 2017, Chang HJ, Chen SL and Lee PY [14] [15] used the Taguchi statistical method to evaluate the direct cutting motion and cutting force analysis of the truncated cone shape model and the pyramid shape model to analyze the machining position fault parameters. The signal-to-noise ratio is obtained by comparing the MA value and the Taguchi method. This promotes the subsequent development of artificial intelligence (AI). In 2018, Han-Jui Chang[16] proposed that RPE can approach the true overall mean under the condition of gradual correction, and used existing evidence to modify existing opinions. Import the data into a five-axis machine tool for performance evaluation to promote subsequent AI development. Use statistical reports to evaluate CNC machine tools with different axes. These reports include direct visual evaluation and fuzzy theoretical operations. These useful and practical evaluation methods are applicable to different types of machine tools, so they can also be used for collaborative processes and overall machine performance evaluation.

In 2019, Chang HJ [17] reviewed various methods for evaluating the performance of five-axis machine tools through identification and multi-type comparison, of which RPE is the most practical. RPE is currently one of the research methods that can obtain accurate reference data through quantitative and identification methods, and it is also one of the evaluation methods for multi-type five-axis machine tool methods. Based on the interface of RPE and IT level distribution in general mechanical design changes, this paper attempts to introduce fuzzy theory to obtain excellent research results. Therefore, we propose and redefine

here: The Recognizable Performance Evaluation (RPE) method has the following characteristics:

- Cross-processing methods "subtractive manufacturing" and "additive manufacturing".
- Cross-workpiece material (such as metal, ceramic, polymer).
- Different physical factors of "cross-processing method and workpiece material" can be identified.
- Can be used as the basis for the subsequent development of artificial intelligence (AI).

In 2020, Han-Jui Chang [18] also proposed a research and implementation method based on the knowledge of molding warpage defects to achieve an identifiable evaluation independent injection molding quality control system. The experiment quantified the interaction between the warping directions of the glass fibers, machines can generate and record data during the production cycle. Although big data management is used, the data can now be processed to obtain troubleshooting methods.

METHODS

Definition of Digital Twin

Digital Twin* is to make full use of physical model, sensor update, operation history and other data, integrate multi-discipline, multi-physical quantity, multi-scale, multi-probability simulation process, complete the mapping in the virtual space, so as to reflect the corresponding The whole life cycle process of the physical equipment. It can be regarded as a digital mapping system of one or more important, interdependent equipment systems. [19].

Fig. 1: Auto interior parts-seat belt guider sample diagram

The most important enlightening significance of the digital twin is that it realizes the feedback of the real physical system to the spatial digital model. In the industrial field, trying to put everything that happens in the physical world back into the digital space. As Fig. 1, only full life tracking with loop feedback is the true concept of full life cycle. In this way, it is possible to ensure the coordination of the digital and physical worlds within the scope of the entire life cycle. Various simulations, analyses, data accumulation, mining, and even the application of artificial intelligence based on digital models can ensure its applicability with real physical systems. This is what the Digital twin means to smart manufacturing [20].

Recognizable Performance Evaluation method

In the product design process, use The functional relationship between quality, cost, and benefit is to develop high-quality products under low-cost conditions." However, the quality benefits and losses based on product development cannot reflect the internal problems that are affected, especially "the unrecognizable factor defects in physical experimental formulas", which often become blind spots in engineering problems.

For "the unrecognizable factor defects in the physical experiment formula", the digital twin experimental application that identifies and compares the contrast in the traditional physics experiment is carried out. Among many experimental projects,

Taguchi can optimize experimental design with appropriately configured experimental recipes and perform Robust analysis of experimental recipes. However, there is no specific statement regarding the "non-recognition of factor defects in the physical experiment formula". The so-called non-recognition refers to the fact that these reference data or experimental results are based on different physical properties or units, but cannot be used in traditional physical experiments. Identify comparative procedures, such as:

"The non-recognition of factor defects in physical experiment formulas" can be divided into three categories:

1. Unitless defect factors: such as entropy, Reynolds number
2. Defect factors of different units: such as length vs angle, temperature vs speed, IT level distribution
3. There are interactive defect factors: such as hardness vs fiber ratio, temperature vs shear force

So, in other words, the biggest difference in the basic thinking of this research is as follows:

- The main research purpose of the "Taguchi Method" is to reduce the "experimental formula" and develop a "high-quality" product at a low cost.
- "Recognizable Evaluation Method" The main research purpose is to define the non-recognition of "factor defects in physical experiment formula".

In addition, "the unrecognizable factor defects in the physical experiment formula" is not only because the unit defects cannot be reflected together, but also the "factor defects" with different "signal-to-noise ratios" can be listed separately. These different "factor defects" The signal-to-noise ratio is fairly simple if it is calculated

independently, but if the defect has more than two types of "signal-to-noise ratio", it is laborious and time-consuming to rely on algorithms to solve it.

As for those defects with more than two kinds of "signal-to-noise ratio characteristics"? In 2021, Chang Han-Jui Chang [21] used the Recognizable Performance Evaluation (RPE) method to obtain accurate reference data for the evaluation of optical components. Among them, the "residual stress defect of optical components" includes more than two types of "signal-to-noise ratio" (Frequency, Tolerance), and the corresponding distribution number (σ -sigma) of each measurement area is determined, so this article tries to introduce Fuzzy theory to obtain excellent research results, and then calculate the attribution level of the measured object. By providing direct differentiation of defuzzification attribution to reduce the interval to manage the distribution income of each frequency distribution, the conflicts in the test performance evaluation that may occur in various fields can be resolved by directly evaluating the prediction results. For a quantifiable performance evaluation, this result further differentiates the landing interval.

Performance evaluation is to pass various tests, conduct various tests on a product, and form an intuitive document, and evaluate the product. One purpose of the evaluation is to provide a reference for the performance indicators of the product, and the performance indicators involve a wide range of areas, are also very complex, and never end. Among for the performance evaluation of products processed by a five-axis machine tool or a 3D printer at the same time, we can refer to the common defects of "subtractive manufacturing" and "additive manufacturing" produced by the products produced by the machine as shown in the Fig. 2: straightness, flatness, The severity of roundness, cylindricity,

parallelism, perpendicularity, inclination, circular deflection, etc... is used to evaluate the quality of the product, but we need to conduct an accurate comparison and analysis of the severity of these defects, and it is Comparative analysis of one-off indicators. The identifiable performance evaluation method here can define an exact and comparable value for the injection molding process parameters of "no unit, different units, multiple vector unit parameters, and multiple interaction vector units", and then perform a reliable quantitative comparison and analysis.

Fig. 2: Auto interior parts-seat belt guider sample diagram

Virtual measurement definition

In 2012, FT Cheng, HC Huang and CA Kao defined [22] : Virtual Metrology (VM) is a method to conjecture manufacturing quality of a process tool based on data sensed from the process tool and without physical metrology operations. as shown in the Fig. 3:

Fig. 3: From $z=0 \sim z$ Trending of normal distribution

Normal distribution curve equation is $P(x) = \frac{\exp[-(x-\mu)^2/(2\sigma^2)]}{\sigma\sqrt{2\pi}}$, μ is mean, σ is SD of normal distribution (as shown Fig. 4).

When $x \geq \mu + z\sigma$, there show as below :

$$F(x \geq \mu + z\sigma) = \int_{u+2\sigma}^{\infty} P(x)dx$$

It's from $x = \mu + z\sigma \sim x = \infty$ which area of curve $P(x)$. And $P(x)$ is symmetric about $x = \mu$. $F(x = \mu + z\sigma)$ and $F(x = \mu - z\sigma)$ is equal :

$$\int_{u+2\sigma}^{\infty} P(x)dx = \int_{-\infty}^{u-2\sigma} P(x)dx$$

Since total area under the curve is 1, then:

$$\int_{-\infty}^{\infty} P(x)dx = 1$$

In order to save costs, the industry currently adopts sampling testing for quality monitoring, but this cannot achieve comprehensive quality control. In order to achieve the goal of comprehensive inspection economically, it is necessary to apply virtual measurement technology.

RESULTS

A very important concept is that the error data must be based on quantitative analysis methods that can be cross-referenced, because "digital twins" and "virtual measurement" allow advanced applications for the performance evaluation of five-axis machine tools. For example, subsequent new cutting evidence of the overall standard deviation of the geometric error of the pyramid test part can modify the standard deviation of the overall tolerance of the test part size (as shown Fig. 4) (as shown Table 1 and Table 2). All previous preparations laid the foundation for the application of cross-reference quantitative analysis techniques.

Fig. 4: Outward Appearance & Dimension of Pyramid Test Part

Table 1: Group Parameters value of Geometric Errors (Additive Manufacturing)

Table 2: Group Parameters value of Geometric Errors(Subtractive Manufacturing)

Calculate the Large best S/N ratio of by formula 1,

$$\frac{S}{N_{\text{望大}}} = -10 \log \frac{\sum_{i=1}^n \frac{1}{y_i^2}}{n} \quad (1)$$

Calculate the Nominal best S/N ratio of by formula 2,

$$\frac{S}{N_{\text{望目}}} = -10 \log \left[\frac{\sum_{i=1}^n (y_i - \bar{y})^2}{n} \right] = -10 \log \left[(\bar{y} - z)^2 + S_n^2 \right] \quad (2)$$

Calculate the Small best S/N ratio of by formula 3,

$$\frac{S}{N_{\text{望小}}} = -10 \log \frac{\sum_{i=1}^n y_i^2}{n} = -10 \log (\bar{y}^2 + S_n^2) \quad (3)$$

Among them: AVE is the average value; SD is the standard deviation. The SN

signal-to-noise ratio relational expression should be adjusted according to the actual conditions of the design standard parts, and the evaluation should be established based on SN-SM, SN-LR or SN-NO. The SN signal-to-noise ratio relational expressions are mainly based on " SN-NO " except for inclination (angle), and the other items are based on " SN-SM ". The following series of relationship lists can be derived. After finishing the calculation, the results are show as Table 3 follows:

Table 3: Compare S/N ratio determine for workpieces

When the above four different types of processing methods are stated in terms of the SN ratio analysis range, the larger the SN ratio, the better the quality (The "V" mark indicates the best item, and the "X" mark indicates the worst item).

Data collection and processing

Before virtual measurement can play a predictive role, it is necessary to collect relevant data in the injection molding process, that is, injection time, measurement time, VP injection switching holding pressure, VP injection switching holding pressure can be collected at the same time in each injection molding cycle Injection molding parameters such as position, injection end point, injection front, measurement time, cycle time, maximum injection speed, etc., as well as any dimensions that can be measured in the injection unit manufacturing process, such as finished product weight or data. Calculate its R total distance, average value, σ standard deviation, CV coefficient of variation, average value, UCL control upper limit, LCL control lower limit and draw the corresponding chart, and draw the average control chart and the data distribution curve of each mode. According to the average control chart, the data distribution curve of each model and the

statistical process control table analysis and interpretation, the results of the injection process under control are obtained, and the control goal of preventing and avoiding waste is achieved in advance.

The measured value control chart can help us implement process control in time when an abnormality is found in the control chart. It is also possible to take process improvement measures when the production process capacity is insufficient, and assign a corresponding σ (sigma) value for each IT level period. It is an effective prevention tool. The purpose of statistical process control is a normal distribution curve, and the average value of the standard deviation (1σ) in each direction will contain 68.25% of the value points. The average willingness of 2σ controls 95.46% of the value points. 3σ usually contains 99.73% value points. Normal $1\sim 3\sigma$ The normal distribution curve is shown in Fig. 5. In this way, the error size and error offset of the parts in the manufacturing process can be standardized, and the σ (Sigma) evaluation value can be given, so that the user of the parts can intuitively select the appropriate error level to achieve the required assembly fit or interchange The range of sex[17].

Fig. 5: 3σ normal distribution

For machine performance monitoring and production process improvement, so that abnormalities can be found in the first time and major losses can be avoided, as shown in Fig. 6.

Fig. 6: Machine performance monitoring and production process improvement

Table 4: Additive Manufacturing of IT tolerance relationship(Pyramid)

Table 5: Subtractive Manufacturing of IT tolerance relationship(Pyramid)

When using an identifiable evaluation method, the overall standard deviation includes the dimensional tolerance of the size of the test part when the event probability E occurs. It is used for several types of "subtractive manufacturing" and "additive manufacturing". You can see that Table 4 is the result of overall additive manufacturing, Table 5 is the result of overall subtractive manufacturing, and the final Total σ (sigma) It represents the σ control value after comparing the DT value of these types of "reduced additive manufacturing" with the experimental value of ET. Table 4 shows that the result of overall additive manufacturing is 53 σ , and Table 5 shows that of overall subtractive manufacturing is 64 σ . It can be judged that "subtractive manufacturing" is easier to control precision than "additive manufacturing". When there are many parts to be compared, the size is different or the size unit is inconsistent, the mass production contrast ratio between the values can be obtained together with the defect rate. At the same time, the simple and intuitive concept is consistent with our initial evaluation concept. But for five-axis machine tool manufacturers, it cannot be regarded as a permanent evaluation result, because researchers always find new methods for continuous improvement. Therefore, when the results of subsequent experiments are released, the yield and defect rates should also be used as reference values to correct the evaluation results.

DISCUSSION

This article is a follow-up extension of the RPE method. Repair parts and post-weld processing cannot be effectively performed on the same platform. Another machine system can be added to the additive

manufacturing process to process existing parts. The processing will generate data for the CAD model version. This data can automatically generate tool paths, conforming to the concept of digital twins, so as to prepare a part for the back and forth conversion between additive and subtractive manufacturing. Our goal is to finally achieve this without any engineering intervention, and to correctly move from one process to the next. At the same time, this technology may also be used to repair parts, otherwise these parts will be scrapped due to machine breakdown or tool breakage in the traditional processing environment. The scrap value is obviously more economical than the repair plan. The user can compare the damaged scan data, and then generate a tool path for additive/subtractive manufacturing to repair the damaged place.

AUTHOR CONTRIBUTIONS

Conceptualization, Han-Jui Chang; Data curation, Shu-Zhou Lu; Methodology, Han-Jui Chang; Project administration, Guang-Yi Zhang; Writing – original draft, Han-Jui Chang.

CREDIT AUTHOR STATEMENT

All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

DATA AVAILABILITY STATEMENT

All data generated or analysed during this study are included in this published article.

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DECLARATIONS

Conflict of interest: The authors declare no conflict of interest.

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Table 1: Group Parameters value of Geometric Errors (Additive Manufacturing).

No.	Measure Item	Ave	SD	SN
1	Straightness	0.0048	0.0026	45.3238
2	Flatness	0.0096	0.0190	33.4330
3	Inclination	0.0047	0.0029	43.6406
4	Inclination(Angle)	0.0569	0.0465	22.6797
5	Parallism	0.0110	0.0225	32.0051
6	Verticality	0.0256	0.0369	26.9558

Table 2: Group Parameters value of Geometric Errors(Subtractive Manufacturing).

No.	Measure Item	Ave	SD	SN
1	Straightness	0.0060	0.0059	41.5090
2	Flatness	0.0096	0.0190	33.4330
3	Inclination	0.0047	0.0029	43.6406
4	Inclination(Angle)	0.0569	0.0465	22.6797
5	Parallism	0.0110	0.0225	32.0051
6	Verticality	0.0256	0.0369	26.9558

Table 3: Compare S/N ratio determine for workpieces.

No.	Measure Item	Subtractive Manufacturing		Additive Manufacturing	
7	Straightness	45.32	V	41.50	X
8	Flatness	54.37	V	33.43	X
9	Inclination	53.83	V	45.22	X
10	Parallism	42.88	V	32.06	X
11	Verticality	26.95	V	24.51	X

12	Inclination(Angle)	65.74	X	68.35	V
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Table 4: Additive Manufacturing of IT tolerance relationship(Pyramid)

Table 5: Subtractive Manufacturing of IT tolerance relationship(Pyramid)

Subtractive Manufacturing	Items	DT	ET	Dev	IT(LSL)	IT(USL)	$\sigma(Sigma)$
	1	98.0000	101.9632	3.9632	16	16	0
	2	86.5000	86.5385	0.0385	12	13	2
	3	76.5000	76.5048	0.0048	8	9	3
	4	56.5000	56.4920	0.0080	9	10	3
	5	36.5000	36.5013	0.0013	5	6	3
	6	17.5000	17.5068	0.0068	9	10	3
	7	21.0000	21.0099	0.0099	10	11	3
	8	41.0000	41.0081	0.0081	9	10	3
	9	61.0000	60.9846	0.0154	10	11	3
	10	81.0000	81.0061	0.0061	8	9	3
	11	91.0000	91.0386	0.0386	12	13	3
	12	100.0000	101.9100	1.9100	16	16	0
	13	5.0000	4.9946	0.0054	10	11	2
	14	12.0000	11.9965	0.0035	8	9	3
	15	10.0000	10.0065	0.0065	9	10	3
	16	10.0000	10.0000	0.0000	01	01	4
	17	6.0000	6.0026	0.0026	8	9	3
	18	3.0000	2.9950	0.0050	10	11	2
	19	3.0000	2.9603	0.0397	14	15	1
	20	5.0000	5.0059	0.0059	10	11	2
	21	12.0000	11.9978	0.0022	7	8	3
	22	10.0000	10.0049	0.0049	9	10	3
	23	10.0000	9.9984	0.0016	6	7	3
	24	6.0000	6.0028	0.0028	8	9	3
	25	3.0000	2.9951	0.0049	10	11	2
	26	3.0000	2.9595	0.0405	14	15	1
Total						64

Figure 1: Auto interior parts-seat belt guider sample diagram.

Figure 2: Auto interior parts-seat belt guider sample diagram.

Figure 3: From $z=0 \sim z$ Trending of normal distribution.

Figure 4: Outward Appearance & Dimension of Pyramid Test Part.

Figure 5: 3σ normal distribution.

Figure 6: Auto interior parts-seat belt guider sample diagram.