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Decision-Making Model of Production Data Management for Multi-Quality Characteristic Products in Consideration of Industry 4.0

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Abstract: According to numerous studies, various parts processed by machine tools usually have multiple-quality characteristics at the same time. Moreover, the process capability index is a handy and useful tool for assessing various quality characteristics. In order to assist downstream customers in evaluating their process capabilities, achieve the effect of integrating the production data of the machine tool industry chain, advance the process quality of products, and reduce rework and scrap, we constructed a shared decision-making model of production data management for multi-quality characteristic products on the cloud platform in consideration of Industry 4.0. This model not only can help downstream customers improve the process for quality characteristics with insufficient process precision or accuracy to figure out the optimum machine parameter setting but also can build a better system of repairs and maintenance. At the same time, all downstream customers' improvement experiences can be gathered to form a knowledge database for improvements and provided to the machine tool industry to set up a complete mechanism of supplier selection, or they can be regarded as a reference for designing superior key components of machine tools, thereby enhancing the product value and industrial competitiveness of machine tools.

Keywords: Industry 4.0; Internet of Things; production data analysis; quality characteristic; process capability index



Citation: Chen, K.-S.; Lin, S.-C.; Lai, K.-K.; Wang, W.-P. Decision-Making Model of Production Data Management for Multi-Quality Characteristic Products in Consideration of Industry 4.0. *Appl. Sci.* **2023**, *13*, 7883. <https://doi.org/10.3390/app13137883>

Academic Editor: Konrad Kulakowski

Received: 10 May 2023

Revised: 30 June 2023

Accepted: 3 July 2023

Published: 5 July 2023



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1. Introduction

A number of studies have revealed that the German government proposed Industry 4.0 in 2011, mainly intending to encourage a comprehensive networking production environment of smart manufacturing through information and communication technologies as well as digital manufacturing technologies [1,2]. Further, numerous studies have considered that as the Internet of Things (IoT) and analytical technology such as Big Data becomes gradually mature, innovation in various industries around the world will be driven [3–6], and the manufacturing industry will stride forward towards smart manufacturing by means of integration and application of related technologies [7–9]. When facing increasingly serious global warming issues, the concept of circular economy (CE) will catalyze the continuous development of innovation and management techniques for enterprises, move towards smart manufacturing and intelligent management, and strive to achieve economic growth as well as environmental sustainability [10,11].

Obviously, what the concept of Industry 4.0 brings the greatest value to the manufacturing industry is that various production data, including machine parameters, process capability analysis, machine maintenance, environmental safety, and energy consumption, are integrated into product design, research and development, and management analysis of

production and process [12,13]. Central Taiwan is an industrial cluster of machine tools, and the value of output and volume of export of machine tools are among the best. Apparently, all kinds of downstream machining factories that purchase machine tools are scattered all over the world, forming an industrial chain of machine tools with Taiwan's machine tool manufacturers and suppliers [14,15]. According to plenty of studies, the components manufactured by machine tools usually have multi-quality characteristics. The quality of finished products can only be ensured when each quality characteristic achieves the required quality level [16,17]. As mentioned above, the Internet of Things (IoT) is becoming more and more popular and mature in the world. If machine tools can build a decision-making model of production data management for multi-quality characteristic products on the cloud platform, this model will contribute to smart manufacturing and intelligent management of the industry.

Many studies have addressed that the process capability index is an accessible and useful tool that the industry uses to assess process quality levels for all types of quality characteristics of products, a communication tool between the sales section and clients, and an effective tool that internal engineers apply to the evaluation and analysis of the process [18,19]. Quite a few studies have depicted process capability indices in the process capability analysis chart, providing the industry with the process capabilities that can simultaneously evaluate all multi-quality characteristics of their products [20,21]. However, the process capability analysis chart proposed by these studies is only suitable for evaluating symmetric tolerances. In practice, the components processed by machine tools have the nominal-the-best quality characteristics, which usually belong to asymmetrical tolerances. To solve this problem, we propose a process capability analysis chart that can simultaneously calculate multiple symmetric tolerances and asymmetric tolerances for products with multiple nominal-the-best quality characteristics. This paper calls this chart Process Capability Analysis Chart with Asymmetric Tolerances, abbreviated to PCAC-AT, for multi-quality characteristic products. With this PCAC-AT, a decision-making model of production data management is established. This decision-making model of production data management can help various machining manufacturers and customers of machine tools to gauge the process capability for each quality characteristic, improve or enhance the process precision and accuracy of quality characteristics, and then find the best machining parameter setting as well as set up a more appropriate machine maintenance system, in order to reduce environmental pollution and energy consumption losses resulting from scrap and rework. Additionally, machine tool makers can gather all downstream customers' experiences of improvements to form an improvement knowledge base, which can be viewed as a reference for the machine tool industry to build a complete supplier selection mechanism or design more quality key components of machine tools, thereby enhancing the product value and industrial competitiveness of machine tools.

Obviously, the advantages of the model proposed in this paper include: (1) It can assist the machining manufacturers, which is the customer end of the machine tool industry chain. In order to evaluate the process capabilities of all important quality characteristics of the processed products. Allowing the processing industry to grasp the overall picture of the processed products and timely improve the quality characteristics of poor quality; (2) It can assist the machine tool industry, collect the improvement experience of all processors, form an improvement knowledge basement, and share it with all machining manufacturers, which is the customer end of the industrial chain; (3) In addition, it can assist the tool industry machinery manufacturers, count all the parts that often go wrong, and give feedback to suppliers or outsourcers to help them improve the quality of the parts they supply; (4) The quality characteristics in the model include symmetrical tolerances and asymmetrical tolerances, in line with the current practice of the machine tool industry. (5) Based on the above, it can assist all members of the machine tool industry chain, including machining manufacturers (customers), machine tool manufacturers, and component suppliers or outsourcers, to reduce carbon emissions by improving quality performance so as to benefit society's responsibility.

Furthermore, a process capability index contains two unknown parameters. If it is evaluated by point estimation directly, then misjudgment is likely to take place due to sampling error [22,23]. Therefore, in this paper, an evaluation coordinate point is built by the interval estimation of two parameters. Because the evaluation coordinate point is built on the confidence interval, it can avoid the misjudgment made by sampling error [24]. In fact, the abscissa of the PCAC-AT analysis chart is the accuracy index, the ordinate is the accuracy index, and the process capability index for evaluating the process quality is a function of these two indexes. For example, if the process capability level is required to be "Capable", then PCAC-AT is a contour map with a process capability index value equal to 1.00. First, you can check the collected product processing data to see if there are extreme values and remove them. Then, considering the position of the evaluation coordinate point of each quality characteristic in the PCAC-AT, we can determine whether to enhance the process of the quality characteristic. The improved method includes adjusting the machine parameters or carrying out the Taguchi test in order to obtain the processing conditions of the best combination of machine parameters.

The other sections are arranged as follows. In Section 2, we build a process capability analysis chart using asymmetric tolerances. Then, we derive the $(1 - \alpha)$ 100% confidence region of process mean and process standard deviation. In Section 3, based on $(1 - \alpha)$ 100% confidence region, an evaluation coordinate point is created. Next, an empirical example is demonstrated to explain the application of the suggested PCAC-AT analysis method in Section 4. Conclusions are made in Section 5. Last, research limitations and future research are in Section 6.

2. Process Capability Analysis Chart with Asymmetric Tolerances

As mentioned above, the process capability index is an accessible and useful tool that the industry applies to gauge the process quality level of each quality characteristic for products. Chan et al. [25] came up with a process capability index named C_{pm} on the basis of the Taguchi loss function. In the index, the denominator is the expectation of the Taguchi loss function so that the process loss can be fully depicted. Further, this index is one of the tools that the manufacturing industry comprehensively applies to the process quality evaluation, defined as follows:

$$C_{pm} = \frac{d}{3\sqrt{\sigma^2 + (\mu - T)^2}}, \quad (1)$$

where μ refers to the process mean, σ represents the process standard deviation, $d = (USL - LSL)/2$ means the half of the specification interval, $T = (USL + LSL)/2$ means the midpoint of the specification limits, USL stands for upper specification limit, and LSL stands for lower specification limit. Plenty of studies have suggested that an unequal relationship is formed between the index C_{pm} and the process yield as the value of the process capability index C_{pm} becomes large enough [26,27]. According to Yu et al. [28], C_{pm} has an unequal relationship with the process yield ($Yield\%$), such that $Yield\% \geq 2\Phi(3C_{pm}) - 1$, where $\Phi(\cdot)$ symbolizes the cumulative distribution function of the standard normal distribution. Thus, since C_{pm} is only suitable for assessing symmetric tolerances, not only can C_{pm} depict the process loss, but it also can fully mirror the process yield. As mentioned earlier, practically, the nominal-the-best quality characteristics of component products processed by machine tools usually belong to asymmetrical tolerances. Thus, Chen et al. [29] put forward a process capability index called C_{pm} with asymmetric tolerances. As noted by some studies, a process has asymmetric tolerances when the upper tolerance $d_U = USL - T$ is unequal to the lower tolerance $d_L = T - LSL$ [30–32]. This asymmetric tolerance index can be shown below:

$$C_{pm}'' = \frac{d^*}{3\sqrt{\sigma^2 + A^2}}, \quad (2)$$

where $A = \text{Max}\{(\mu - T)d^*/d_U, (T - \mu)d^*/d_L\}$ and $d^* = \text{Min}\{d_U, d_L\}$. Apparently, when the preset target value $T = (\text{USL} + \text{LSL})/2 = M$ (symmetric case), then $d^* = d$, $A = |\mu - T|$, and the asymmetric tolerance index C''_{pk} will drop to the original index C_{pk} . In the definition, factor A guarantees that C''_{pk} can reach its maximal value at $\mu = T$ (on-target process) no matter if the tolerance is symmetric ($T = M$) or asymmetric ($T \neq M$). Let $\gamma = \sigma/d^*$ and

$$C''_{pm} = \frac{d^*}{3\sqrt{\sigma^2 + A^2}} \tag{3}$$

where $\delta' = (\mu - T)/d^*$, $d_1 = d^*/d_U$, and $d_2 = d^*/d_L$. Then

$$C''_{pm} = \frac{1}{3\sqrt{\gamma^2 + \delta^2}} \tag{4}$$

When $\delta = 0$, it means that the process average μ is just located at the target value T . When $\delta > 0$, it shows that the process is shifted to the right. For example, when $\delta = 1/4$, it indicates that the process average μ is shifted to the right by $1/4$ tolerance from the target value T . When $\delta < 0$, then the process is shifted to the left. For instance, when $\delta = -1/2$, then the process average μ is shifted to the left by $1/2$ tolerance from the target value T .

As mentioned earlier, usually multiple important quality characteristics exist in a product after it is processed. When the process quality of all quality characteristics attains the required quality level, then the product's process quality can be ensured to meet customer demand. Without losing generality, it is assumed that there are k quality characteristics of the product in this paper.

Based on Chen et al. [33], if we require that the value of the process capability index C''_{PMT} should be at least C_T , then the value of the process capability index C''_{pmh} of the quality characteristic h should be required to be at least C as well, where $h = 1, 2, \dots, k$. The relationship can be defined below:

$$C = \frac{1}{3} \Phi^{-1} \left\{ 1 - \frac{1 - \Phi(3C_T)}{k} \right\} \tag{5}$$

When $C''_{pmh} = C$, we have $\gamma_h^2 + \delta_h^2 = 1/(3C)^2$, where $\delta_h = \delta'_h d_{h1}$ for $\mu_h \geq T_h$ and $\delta_h = \delta' d_2$ for $\mu_h < T_h$. Next, this paper takes δ as abscissa (x-axis) and γ as ordinate (y-axis). Based on the above-stated, the process capability analysis chart with asymmetric tolerances can be depicted in Figure 1 as follows:

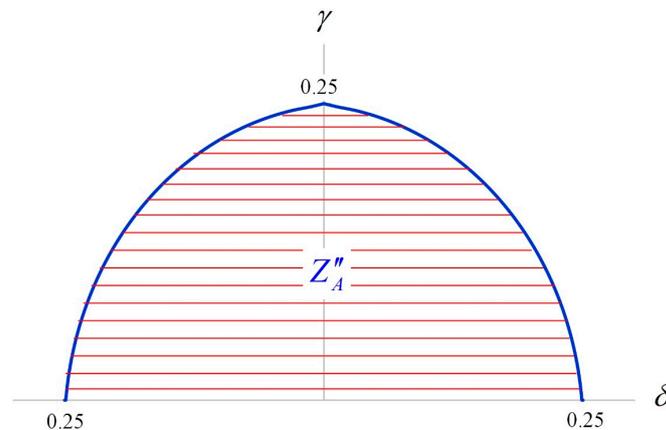


Figure 1. Process Capability Analysis Chart with Asymmetric Tolerances.

As the value of the process capability index C_{PMT}'' is required to be C_T , the value of process capability index C_{pmh}'' is required to be C for each quality characteristic. Thus, we define the process capability accept zone Z_A'' as follows:

$$Z_A'' = \left\{ (\delta_h, \gamma_h) \mid \gamma_h^2 + \delta_h^2 = 1/(3C)^2, \gamma_h \geq 0 \right\}. \tag{6}$$

Obviously, when the pair of process mean and process standard for quality characteristic h belong to zone Z_A'' , that is $(\delta_h, \gamma_h) \in Z_A''$, then the process capability attains the required quality level ($C_{pmh}'' \geq C$). When $(\delta_h, \gamma_h) \notin Z_A''$, then the process capability is below the required quality level ($C_{pmh}'' < C$). Therefore, the process quality needs to be ameliorated. Both the process mean and the process standard are unknown parameters; therefore, sample data need to be gauged. Numerous studies have indicated that the point estimation is prone to wrong judgment incurred by sampling error. As a result, we derive the $100(1 - \alpha)\%$ confidence region of (δ_h, γ_h) based on sample data in the next section. Based on the process capability analysis chart and the $100(1 - \alpha)\%$ confidence region of (δ_h, γ_h) , we construct the measurement coordinate point of quality characteristic h .

In fact, the abscissa of the PCAC-AT analysis diagram is the accuracy index, the ordinate is the accuracy index, and the accept zone Z_A'' is the contour line of $C_{pmh}'' = C$. According to the position of each evaluation coordinate point, the deviation or variation of the process of the quality characteristic can be directly observed, so it is possible to grasp the overall picture of the processed product and the opportunity for improvement.

3. Construct the Measurement Coordinate Point

This article established the PCAC-AT analysis chart in Section 2 and then will establish the rules based on the analysis chart of Section 2, and then construct the evaluation coordinate points of each quality characteristic according to the principle of statistical inference and evaluation rules. Let $X_{h,1}, \dots, X_{h,n}$ be a random sample derived from quality characteristic h with sample size n , where $h = 1, 2, \dots, k$. Then the estimators of μ_h is

$$\bar{X}_h = \frac{1}{n} \sum_{j=1}^n X_{h,j} \text{ and the estimators of } \sigma_h \text{ is } S_h = \sqrt{\frac{1}{n} \sum_{j=1}^n (X_{h,j} - \bar{X}_h)^2}.$$

Therefore, the estimators of index δ'_h is $\hat{\delta}'_h = (\bar{X}_h - T_h)/d_h^*$ and the estimators of index γ'_h is $\hat{\gamma}'_h = S_h/d_h^*$. With an assumption of normality, $T_h = \sqrt{n}(\hat{\delta}'_h - \delta'_h)/\hat{\gamma}'_h$ is distributed as a t-distribution with $n-1$ degree of freedom, denoted by t_{n-1} , and $K_h = n\hat{\gamma}'_h/\gamma_h^2$ is distributed as a chi-square distribution with $n-1$ degree of freedom, denoted by χ_{n-1}^2 . Since the probability that T_h between $-t_{1-\alpha/4;n-1}$ and $t_{1-\alpha/4;n-1}$ is $1 - \alpha/2$, where $t_{\alpha/4;n-1}$ is the upper $\alpha/4$ quintile of t_{n-1} . Therefore, the $1 - \alpha/2$ lower confidence limit of δ'_h is $\hat{\delta}'_h - e_h$ and the $1 - \alpha/2$ upper confidence limit of δ'_h is $\hat{\delta}'_h + e_h$, where $e_h = t_{\alpha/4;n-1}\hat{\gamma}'_h/\sqrt{n}$.

Similarly, since probability that K_h between $\chi_{\alpha/4;n-1}^2$ and $\chi_{1-\alpha/4;n-1}^2$ is $1 - \alpha/2$, where $\chi_{\alpha/4;n-1}^2$ is the lower $\alpha/4$ quintile of χ_{n-1}^2 , and $\chi_{1-\alpha/4;n-1}^2$ is the lower $1 - \alpha/4$ quintile of χ_{n-1}^2 . Therefore, the $1 - \alpha/2$ lower confidence limit of γ'_h is γ'_{Lh} and the $1 - \alpha/2$ upper confidence limit of γ'_h is γ'_{Uh} , where $\gamma'_{Lh} = \sqrt{n/\chi_{1-\alpha/4;n-1}^2}\hat{\gamma}'_h$ and $\gamma'_{Uh} = \sqrt{n/\chi_{\alpha/4;n-1}^2}\hat{\gamma}'_h$.

Obviously, when $\hat{\delta}'_h - e_h \geq 0$, it can be inferred that $\delta'_h \geq 0$ and $\mu_h \geq T_h$. Likewise, when $\hat{\delta}'_h + e_h < 0$, it can be inferred that $\delta'_h < 0$ and $\mu_h < T_h$. Thus,

$$\hat{\delta}_h = \begin{cases} \hat{\delta}'_h d_{h1}, \hat{\delta}'_h - e_h \geq 0 \\ \hat{\delta}'_h d_{h2}, \hat{\delta}'_h + e_h < 0 \end{cases}. \tag{7}$$

In order to derive the $100(1 - \alpha)\%$ confidence region of (δ'_h, γ'_h) , this paper defines events $E_{\delta h} = \{\delta'_{Lh} \leq \delta'_h \leq \delta'_{Uh}\}$ and $E_{\gamma h} = \{\gamma'_{Lh} \leq \gamma'_h \leq \gamma'_{Uh}\}$.

Obviously, $p(E_{\delta h}) = p(E_{\gamma h}) = 1 - \alpha/2$ and $p(E_{\delta h}^C) = p(E_{\gamma h}^C) = \alpha/2$. Based on Boole's inequality and DeMorgan's rules, we have $p(E_{\delta h} \cap E_{\gamma h}) \geq 1 - p(E_{\delta h}^C) - p(E_{\gamma h}^C)$

$= \alpha/2$. Then, $CR = \{(\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h1} \leq \delta_h \leq \delta'_{Uh} \times d_{h1}, \gamma'_{Lh} \times d_{h1} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h1}\}$, where $\hat{\gamma}_h = \hat{\gamma}'_h d_{h1}$, $\hat{\delta}_h = \hat{\delta}'_h d_{h1}$. is the $100(1 - \alpha)\%$ confidence region of (δ_h, γ_h) for $\hat{\delta}'_{Lh} \geq 0$. Similarly, $\hat{\delta}_h = \hat{\delta}'_h d_{h2}$ for $\hat{\delta}'_{Uh} < 0$, then, $100(1 - \alpha)\%$ confidence region of (δ_h, γ_h) is $CR = \{(\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h2} \leq \delta_h \leq \delta'_{Uh} \times d_{h2}, \gamma'_{Lh} \times d_{h2} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h2}\}$ for $\hat{\delta}'_{Uh} < 0$, where $\gamma_h = \gamma'_h d_{h2}$ and $\delta_h = \delta'_h d_{h2}$. Based on the above-stated, the $100(1 - \alpha)\%$ confidence region of (δ_h, γ_h) is expressed as:

$$CR = \begin{cases} \{(\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h1} \leq \delta_h \leq \delta'_{Uh} \times d_{h1}, \gamma'_{Lh} \times d_{h1} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h1}\}, \delta'_{Lh} \geq 0 \\ \{(\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h2} \leq \delta_h \leq \delta'_{Uh} \times d_{h2}, \gamma'_{Lh} \times d_{h2} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h2}\}, \delta'_{Uh} < 0 \end{cases} \quad (8)$$

Obviously, since the intersection of zone (Z''_A) and the confidence region (CR) are not empty sets, it can be deduced that the value of the process capability index C''_{pk} is larger than or equivalent to C ($C''_{pk} \geq C$). Based on this concept, we can create the measurement coordinate point (x_h, y_h) of quality characteristic h as follows (see Appendix A):

$$(x_h, y_h) = \begin{cases} (\delta_{Lh}, \gamma_{Lh}) = \left(\left(\hat{\delta}'_h - \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \right) \times d_{h1}, \sqrt{\frac{n}{\chi^2_{1-\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h1} \right), \delta'_{Lh} \geq 0 \\ (\delta_{Uh}, \gamma_{Uh}) = \left(\left(\hat{\delta}'_h + \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \right) \times d_{h2}, \sqrt{\frac{n}{\chi^2_{\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h2} \right), \delta'_{Uh} < 0 \end{cases} \quad (9)$$

Then, the process quality of the quality characteristic h is measured by the location of the coordinate point. Decision-making rules for the measurement are listed as follows:

When $(x_h, y_h) \in Z''_A$, then the value of index C''_{pmh} is bigger than C , and the process capability of quality characteristic h attains the required level.

When $(x_h, y_h) \notin Z''_A$, then the value of index C''_{pmh} is smaller than C , and the process capability of quality characteristic h is under the required level. The process capability of quality characteristic h needs to be leveled up. This quality characteristic is regarded as critical to quality (CTQ) in this paper.

4. An Empirical Example

As mentioned above, the central part of Taiwan is an industrial cluster of machine tools, and the value of output and the volume of export of machine tools are both among the best. Usually, components processed by machine tools are simultaneously equipped with multiple quality characteristics. The quality of finished goods can only be ensured when each quality characteristic conforms to the required level of quality. It will contribute to smart manufacturing and intelligent management of the machine tool industry to apply a decision-making model of production data management for multi-quality characteristic products built in the second and third sections of this paper as well as conduct the process capability evaluation of each quality characteristic with the production data of the components processed by machining factories through the Internet of Things and cloud platforms.

The components processed by a machining factory have a total of four important quality characteristics, including inner diameter, outer diameter, length, and weight. According to Equation (5), when the value of the process capability index C''_{PMT} is set to be at least 1.0 ($C_T = 1.0$), then the required value of index C''_{pmh} is at least 1.133 ($C = 1.133$) for each quality characteristic. Thus, the process capability accept zone Z''_A is defined as

$$Z''_A = \left\{ (\delta_h, \gamma_h) | \gamma_h^2 + \delta_h^2 = 1/(4.5)^2, \gamma_h \geq 0 \right\}$$

In addition, the units and tolerance specifications for these four important quality characteristics are illustrated in Table 1 below:

Table 1. Units and Tolerances of Four Important Quality Characteristics.

Quality Characteristic	Tolerance	Unit
1. Inner Diameter	$1.2^{+0.03}_{-0.01}$	mm
2. Outer Diameter	$1.8^{+0.02}_{-0.03}$	mm
3. Length	30 ± 0.03	mm
4. Weight	12 ± 0.05	mg

The sample mean and sample standard of random samples from four quality characteristics with sample size $n = 36$ can be displayed as follows:

$$\delta = \begin{cases} \delta' d_1, \mu \geq T \\ \delta' d_2, \mu < T \end{cases} ,$$

where $\delta' = (\mu - T)/d^*$, $d_1 = d^*/d_U$, and $d_2 = d^*/d_L$. Then,

quality characteristic 1: ($T_1 = 1.2$, $d_{L1} = 0.01$, $d_{U1} = 0.03$, $d_1^* = 0.01$, $d_{11} = 1/3$, $d_{12} = 1$), $\bar{X}_1 = 1.201$ and $S_1 = 0.002$;

quality characteristic 2: ($T_2 = 1.8$, $d_{L2} = 0.03$, $d_{U2} = 0.02$, $d_2^* = 0.02$, $d_{21} = 1$, $d_{22} = 2/3$), $\bar{X}_2 = 1.796$ and $S_2 = 0.005$;

quality characteristic 3: ($T_3 = 30$, $d_{L3} = 0.05$, $d_{U3} = 0.05$, $d_3^* = 0.05$, $d_{31} = 1$, $d_{32} = 1$), $\bar{X}_3 = 30.02$ and $S_3 = 0.005$;

quality characteristic 4: ($T_4 = 12$, $d_{L4} = 0.1$, $d_{U4} = 0.1$, $d_4^* = 0.1$, $d_{41} = 1$, $d_{42} = 1$), $\bar{X}_4 = 12.01$ and $S_4 = 0.01$.

Therefore, the value of estimators for index δ'_h and index γ'_h are expressed as follows:

quality characteristic 1: $\delta'_1 = 0.2$ and $\gamma'_1 = 0.2$;

quality characteristic 2: $\delta'_2 = -0.2$ and $\gamma'_2 = 0.25$;

quality characteristic 3: $\delta'_3 = 0.4$ and $\gamma'_3 = 0.167$;

quality characteristic 4: $\delta'_4 = 0.2$ and $\gamma'_4 = 0.2$.

In fact, the value of the upper 0.0025 quintile of t_{35} is 2.996 ($t_{0.0025,35} = 2.996$). Then, based on Equation (A11), this paper will calculate the value of measurement coordinate point for four quality characteristics and show as follows:

quality characteristic 1: The value of $[\delta'_{L1}, \delta'_{U1}]$ is $[-0.325, -0.075]$. Thus, the value of δ'_{L1} is bigger than zero ($\delta'_{L1} = 0.1 \geq 0$), and the measurement coordinate point is

$$(x_1, y_1) = (\delta_{L1}, \gamma_{L1}) = (0.033, 0.050).$$

quality characteristic 2: The value of $[\delta'_{L2}, \delta'_{U2}]$ is $[0.1, 0.3]$. Thus, the value of δ'_{U2} is smaller than zero ($\delta'_{U2} = -0.75 < 0$), and the measurement coordinate point is

$$(x_2, y_2) = (\delta_{U2}, \gamma_{L2}) = (-0.05, 0.126).$$

quality characteristic 3: The value of is $[\delta'_{L3}, \delta'_{U3}]$ is $[0.315, 0.485]$. Thus, the value of δ'_{L3} is bigger than zero ($\delta'_{L3} = 0.315 \geq 0$), and the measurement coordinate point is

$$(x_3, y_3) = (\delta_{L3}, \gamma_{L3}) = (0.315, 0.126).$$

quality characteristic 4: The value of $[\delta'_{L4}, \delta'_{U4}]$ is $[0.100, 0.300]$. Thus, the value of δ'_{L4} is bigger than zero ($\delta'_{L4} = 0.300 \geq 0$), and the measurement coordinate point is

$$(x_4, y_4) = (\delta_{L4}, \gamma_{L4}) = (0.100, 0.151).$$

According to the above calculation results, the evaluation coordinate points of the four quality characteristics are depicted in Figure 2 below:

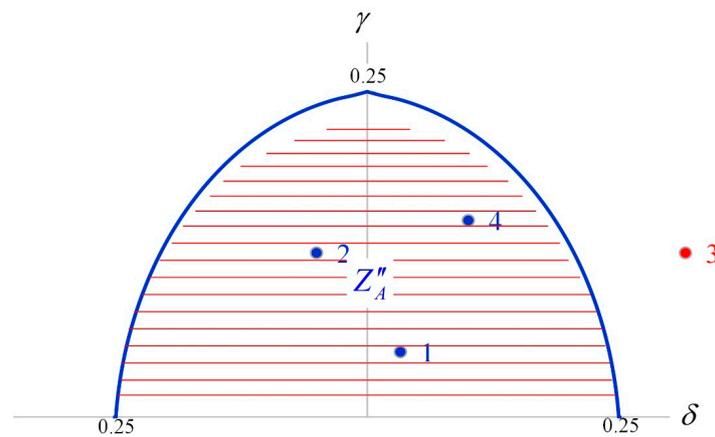


Figure 2. PCAC-AT for Product with Four Quality Characteristics.

In Figure 2, the evaluation coordinate point of quality characteristic three does not belong to zone Z''_A ($(x_3, y_3) \notin Z''_A$), then the value of C_{pm3} is smaller than 1.133. The process capability of quality characteristic three needs to make improvements. For quality characteristic 3, $\hat{\gamma}_3 = 1/6$ means that the process variation is small and the precision has reached six-sigma, while $\hat{\delta}_3 = 0.4$ indicates that the process is seriously shifted to the right, so the poor process capability is caused by the right skewness of the process, and it may be necessary to adjust the machine parameters.

Machine tool manufacturers can collect relevant data for this evaluation and improvement. In the meantime, the relevant data of all machining factories which purchase machine tools can be sorted out to form a process capability improvement database. The database can be offered to all customers who purchase machine tools to help them make improvements in their processes. Additionally, the machine tool industry can collect the improvement experience of all machining manufacturers, form an improvement knowledge basement, and share it with the machining manufacturers, which is the customer end of the industrial chain. In addition, machine tool manufacturers can also count all the parts that often go wrong and give feedback to suppliers or outsourcers to help them improve the quality of the parts they supply.

5. Conclusions

Many studies have pointed out that the output value and the export volume of Taiwan's machine tools both come out among the best. Various downstream machining factories that purchase machine tools are scattered all over the world, forming an industrial chain of machine tools with Taiwan's machine tool makers and suppliers. According to numerous studies, multiple quality characteristics usually exist simultaneously in all components processed by machine tools. Moreover, under the condition that the sound environment of the Internet of Things (IoT) and analytical technology such as Big Data become gradually mature, we adopted process capability indicators to depict a process capability evaluation and analysis chart with multiple quality characteristics in this paper. This evaluation and analysis chart can simultaneously evaluate process capabilities of quality characteristics for products, including symmetric tolerances and asymmetric tolerances. In order to achieve such a function, the process precision index was set as δ_h , and the process accuracy index was set as γ_h for the asymmetric tolerances of the quality characteristic h by means of variable transformation. Moreover, we used the $100(1 - \alpha)\%$ confidence region of these two indexes and applied the principle of statistical inference to set up the evaluation coordinate point (x_h, y_h) of the quality characteristic h . It allows process engineers to not only position the evaluation coordinate point (x_h, y_h) of each quality characteristic h on the process capability analysis chart but also grasp the accuracy and precision of the process for each quality characteristic. Next, following the evaluation criteria, we decided whether to carry out process improvement and determined the improvement direction based on

the evaluation coordinate point (x_h, y_h) . The above-mentioned decision-making model of production data management for multi-quality products can be built on the cloud platform to help downstream customers in the machine tool industry chain improve their processes to figure out the best machine parameter setting for quality characteristics with insufficient process precision or accuracy as well as help them establish a better system of machine repairs and maintenance. In the meantime, all downstream customers' improvement experiences can be gathered and shaped into an improvement knowledge base, providing the machine tool industry with a complete mechanism for the supplier selection or reference for designing better quality key components of machine tools, thereby raising the product value and industrial competitiveness of machine tools as well as moving towards the goal of smart manufacturing.

6. Research Limitations and Future Research

As mentioned above, the model proposed in this paper can assist the machining manufacturers, which is the customer end of the machine tool industry chain, to evaluate the process capability of all important quality characteristics of the processed products so that the machining manufacturers can grasp the overall picture of the processed products and improve the poor quality in time quality characteristics. In addition, when the entire machine tool industry chain uses this model for a period of time, the machine tool industry can collect the improvement experience of all machining manufacturers, form an improvement knowledge basement, and share it with all machine tool manufacturers at the customer end of the industry chain. Feedback on the problematic parts and components for suppliers or outsourcers to help them improve the quality of supplied parts and components. Due to the itinerary and sharing of the knowledge basement, the problems and feedback of common components not only need a long time to collect and build but also a complex problem. This study focuses on the process capability evaluation and improvement model for multi-quality characteristic products. The establishment and application of the other issues can be the focus of future research.

Author Contributions: Conceptualization, K.-S.C. and K.-K.L.; methodology, K.-S.C. and K.-K.L.; software, S.-C.L. and W.-P.W.; validation, S.-C.L. and W.-P.W.; formal analysis, K.-S.C. and K.-K.L.; resources, S.-C.L.; data curation, S.-C.L. and W.-P.W.; writing—original draft preparation, K.-S.C., S.-C.L., K.-K.L. and W.-P.W.; writing—review and editing, K.-S.C. and K.-K.L.; visualization, S.-C.L.; supervision, K.-S.C.; project administration, K.-K.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: All data underlying the results are available as part of the article and no additional source data are required.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The measurement coordinate point (x_h, y_h) of quality characteristic h as follows:

$$(x_h, y_h) = \begin{cases} (\delta_{Lh}, \gamma_{Lh}) = \left(\left(\hat{\delta}'_h - \frac{t_{\alpha/4; n-1}}{\sqrt{n}} \hat{\gamma}'_h \right) \times d_{h1}, \sqrt{\frac{n}{\lambda_{1-\alpha/4; n-1}^2}} \hat{\gamma}'_h \times d_{h1} \right), \delta'_{Lh} \geq 0 \\ (\delta_{Uh}, \gamma_{Uh}) = \left(\left(\hat{\delta}'_h + \frac{t_{\alpha/4; n-1}}{\sqrt{n}} \hat{\gamma}'_h \right) \times d_{h2}, \sqrt{\frac{n}{\lambda_{\alpha/4; n-1}^2}} \hat{\gamma}'_h \times d_{h2} \right), \delta'_{Uh} < 0 \end{cases} \tag{A1}$$

Proof:

Let $X_{h,1}, \dots, X_{h,n}$ be a random sample derived from quality characteristic h with sample size n , where $h = 1, 2, \dots, k$. Then estimators of μ_h and σ_h are expressed as follows:

$$\bar{X}_h = \frac{1}{n} \sum_{j=1}^n X_{h,j} \tag{A2}$$

and

$$S_h = \sqrt{\frac{1}{n} \sum_{j=1}^n (X_{h,j} - \bar{X}_h)^2} \tag{A3}$$

Therefore, the estimators of index δ'_h and index γ'_h are displayed below:

$$\delta'_h = \frac{\bar{X}_h - T_h}{d_h^*} \tag{A4}$$

and

$$\hat{\gamma}'_h = \frac{S_h}{d_h^*} \tag{A5}$$

With an assumption of normality, $\sqrt{n}(\delta'_h - \delta'_h) / \hat{\gamma}'_h$ is distributed as t-distribution with $n-1$ degree of freedom, denoted by t_{n-1} , and $n\hat{\gamma}'_h{}^2 / \gamma_h{}^2$ is distributed as chi-square distribution with $n-1$ degree of freedom, denoted by χ_{n-1}^2 . Therefore,

$$p\left(-t_{\alpha/4;n-1} \leq \frac{\sqrt{n}(\hat{\delta}'_h - \delta'_h)}{\hat{\gamma}'_h} \leq t_{\alpha/4;n-1}\right) = p(\delta'_h - e_h \leq \delta'_h \leq \delta'_h + e_h) = 1 - \frac{\alpha}{2}, \tag{A6}$$

where $e_h = t_{\alpha/4;n-1} \hat{\gamma}'_h / \sqrt{n}$ and $t_{\alpha/4;n-1}$ is the upper $\alpha/4$ quintile of t_{n-1} . Similarly,

$$p\left(\chi_{\alpha/4;n-1}^2 \leq \frac{n\hat{\gamma}'_h{}^2}{\gamma_h{}^2} \leq \chi_{1-\alpha/4;n-1}^2\right) = p\left(\sqrt{\frac{n}{\chi_{1-\alpha/4;n-1}^2}} \hat{\gamma}'_h \leq \gamma'_h \leq \sqrt{\frac{n}{\chi_{\alpha/4;n-1}^2}} \hat{\gamma}'_h\right) = 1 - \frac{\alpha}{2}, \tag{A7}$$

where $\chi_{\alpha/4;n-1}^2$ is the lower $\alpha/4$ quintile of χ_{n-1}^2 , and $\chi_{1-\alpha/4;n-1}^2$ is the lower $1 - \alpha/4$ quintile of χ_{n-1}^2 . Obviously, when $\hat{\delta}'_h - e_h \geq 0$, it can be inferred that $\delta'_h \geq 0$ and $\mu_h \geq T_h$. Likewise, when $\hat{\delta}'_h + e_h < 0$, it can be inferred that $\delta'_h < 0$ and $\mu_h < T_h$. Thus,

$$\delta_h = \begin{cases} \hat{\delta}'_h d_{h1}, \hat{\delta}'_h - e_h \geq 0 \\ \hat{\delta}'_h d_{h2}, \hat{\delta}'_h + e_h < 0 \end{cases} \tag{A8}$$

In order to derive the $100(1 - \alpha)\%$ confidence region of (δ'_h, γ'_h) , this paper defines events $E_{\delta h}$ and $E_{\gamma h}$ as follows:

$$E_{\delta h} = \{\delta'_{Lh} \leq \delta'_h \leq \delta'_{Uh}\} = \left\{ \hat{\delta}'_h - \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \leq \delta'_h \leq \hat{\delta}'_h + \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \right\} \tag{A9}$$

$$E_{\gamma h} = \{\gamma'_{Lh} \leq \gamma'_h \leq \gamma'_{Uh}\} = \left\{ \sqrt{\frac{n}{\chi_{1-\alpha/4;n-1}^2}} \hat{\gamma}'_h \leq \gamma'_h \leq \sqrt{\frac{n}{\chi_{\alpha/4;n-1}^2}} \hat{\gamma}'_h \right\} \tag{A10}$$

Obviously, $p(E_{\delta h}) = p(E_{\gamma h}) = 1 - \alpha/2$ and $p(E_{\delta h}^C) = p(E_{\gamma h}^C) = \alpha/2$. Based on Boole's inequality and DeMorgan's rules, we have $p(E_{\delta h} \cap E_{\gamma h}) \geq 1 - p(E_{\delta h}^C) - p(E_{\gamma h}^C) = \alpha/2$. Thus,

$$p\left\{ \hat{\delta}'_h - \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \leq \delta'_h \leq \hat{\delta}'_h + \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h, \sqrt{\frac{n}{\chi_{1-\alpha/4;n-1}^2}} \hat{\gamma}'_h \leq \gamma'_h \leq \sqrt{\frac{n}{\chi_{\alpha/4;n-1}^2}} \hat{\gamma}'_h \right\} = 1 - \alpha. \tag{A11}$$

Based on Equation (A8), $\hat{\delta}_h = \hat{\delta}'_h d_{h1}$ for $\hat{\delta}'_{Lh} \geq 0$, then

$$p \left\{ \hat{\delta}'_h \times d_{h1} - \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \times d_{h1} \leq \delta_h \leq \hat{\delta}'_h \times d_{h1} + \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \times d_{h1} \right. \\ \left. \sqrt{\frac{n}{\chi^2_{1-\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h1} \leq \gamma_h \leq \sqrt{\frac{n}{\chi^2_{\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h1} \right\} = 1 - \alpha, \tag{A12}$$

where $\hat{\gamma}_h = \hat{\gamma}'_h d_{h1}$, $\delta_h = \delta'_h d_{h1}$. Therefore, 100(1 - α)% confidence region of (δ_h, γ_h) for $\hat{\delta}'_{Lh} \geq 0$ is expressed as:

$$CR = \{ (\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h1} \leq \delta_h \leq \delta'_{Uh} \times d_{h1}, \gamma'_{Lh} \times d_{h1} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h1} \}. \tag{A13}$$

Similarly, $\hat{\delta}_h = \hat{\delta}'_h d_{h2}$ for $\hat{\delta}'_{Uh} < 0$, then

$$p \left\{ \hat{\delta}'_h \times d_{h2} - \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \times d_{h2} \leq \delta_h \leq \hat{\delta}'_h \times d_{h2} + \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \times d_{h2}, \right. \\ \left. \sqrt{\frac{n}{\chi^2_{1-\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h2} \leq \gamma_h \leq \sqrt{\frac{n}{\chi^2_{\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h2} \right\} = 1 - \alpha \tag{A14}$$

where $\hat{\gamma}_h = \hat{\gamma}'_h d_{h2}$, $\delta_h = \delta'_h d_{h2}$. Therefore, 100(1 - α)% confidence region of (δ_h, γ_h) for $\hat{\delta}'_{Uh} < 0$ is displayed as:

$$CR = \{ (\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h2} \leq \delta_h \leq \delta'_{Uh} \times d_{h2}, \gamma'_{Lh} \times d_{h2} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h2} \}. \tag{A15}$$

Based on the above-stated, the 100(1 - α)% confidence region of (δ_h, γ_h) is expressed as:

$$CR = \left\{ \begin{array}{l} \{ (\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h1} \leq \delta_h \leq \delta'_{Uh} \times d_{h1}, \gamma'_{Lh} \times d_{h1} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h1} \}, \delta'_{Lh} \geq 0 \\ \{ (\delta_h, \gamma_h) | \delta'_{Lh} \times d_{h2} \leq \delta_h \leq \delta'_{Uh} \times d_{h2}, \gamma'_{Lh} \times d_{h2} \leq \gamma_h \leq \gamma'_{Uh} \times d_{h2} \}, \delta'_{Uh} < 0 \end{array} \right. \tag{A16}$$

Obviously, since the intersection of zone (Z''_A) and the confidence region (CR) are not empty sets, it can be deduced that the value of process capability index C''_{pk} is larger than or equivalent to C ($C''_{pmh} \geq C$). Based on this concept, we can create the measurement coordinate point (x_h, y_h) of quality characteristic h as follows:

$$(x_h, y_h) = \begin{cases} (\delta_{Lh}, \gamma_{Lh}) = \left(\left(\hat{\delta}'_h - \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \right) \times d_{h1}, \sqrt{\frac{n}{\chi^2_{1-\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h1} \right), \delta'_{Lh} \geq 0 \\ (\delta_{Uh}, \gamma_{Lh}) = \left(\left(\hat{\delta}'_h + \frac{t_{\alpha/4;n-1}}{\sqrt{n}} \hat{\gamma}'_h \right) \times d_{h2}, \sqrt{\frac{n}{\chi^2_{\alpha/4;n-1}}} \hat{\gamma}'_h \times d_{h2} \right), \delta'_{Uh} < 0 \end{cases} \tag{A17}$$

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