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Implementing Process Capability Index (*Cpk*) for Effective Product Quality Stabilization: The Case of a Lock Manufacturing Company

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In computer numerical control (CNC) production, product specifications are entered into machine software, and sensors automatically distinguish between conforming and nonconforming products, preventing mixing and shipment issues. Modern factories often use sensor-based automated measurement instruments to improve efficiency and reduce costs. Process capability indices (e.g., *Cp*, *Cpk*, and *Cpm*) quantify process variability relative to specifications, with *Cpk* widely used owing to its focus on aligning the process mean with the specification center. In this study, we explored product quality stabilization by using *Cpk* to analyze sensor data in lock manufacturing, stabilizing product quality, and verifying process stability after equipment maintenance to make the material inspections more accurate. We selected key dimensions of lock products for measurement, employing an image-measuring instrument for bi-daily sampling. Analysis results indicate that *Cpk* effectively reflects process stability. If the *Cpk* value does not reach $\geq$1.33, CNC lathe parameters are adjusted to enhance the *Cpk* value, demonstrating significant process capability improvement. Additionally, we innovatively applied *Cpk* to evaluate process capability post-equipment maintenance, ensuring that product quality meets the required standards. In summary, we demonstrated the practicality and effectiveness of *Cpk* in process capability assessment and improvement.

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1. Introduction

In today's highly competitive market, the challenge is to produce high-quality products at the lowest cost while maintaining a leading position. An "industrial process" is a unique combination of machines, materials, methods, and personnel producing measurable outputs.(1) Process capability is a measurable attribute of a process relative to its specifications. This measurement output can predict the number of units produced out of specification.(2,3) Process capability analysis, alongside the statistical process control and design of experiments, has been utilized for decades as a statistical methodology aimed at reducing variability in industrial processes and products.(4) Process capability analysis involves evaluating the capability of a manufacturing process and using process information to improve that capability. It allows for determining how well a process performs relative to product requirements or specifications. Before evaluating process capability, it is essential to ensure that the process is stable and repeatable. Statistical process control is typically applied to check process stability, enabling the detection and elimination of assignable causes of variation.(5) Control charts are commonly used to determine whether a process is under statistical control and reveal systematic process output patterns.(6)

Precision manufacturing is a method that emphasizes extremely high accuracy and quality control throughout the production process.(7) Such manufacturing is typically applied in scenarios with stringent dimensions, tolerances, and surface roughness requirements, such as in the aerospace, medical device, and precision machinery industries. The main characteristics of precision manufacturing include high-precision equipment and highly sensitive sensors and tools, such as the utilization of high-precision machinery (e.g., computer numerical control (CNC) machines and advanced measuring instruments).(8,9) Strict quality control such as implementing rigorous quality control measures throughout the production process ensures that each manufacturing stage meets the predetermined quality standards. A narrow tolerance range, such as a minimal manufacturing tolerance range, necessitates precise control throughout the production process. Advanced manufacturing techniques use the latest manufacturing technologies and materials to enhance product performance and production efficiency.

Understanding processes and quantifying performance are crucial for any successful quality improvement program. The relationship between actual process performance and specification limits or tolerances can be quantified using appropriate process capability indices. In the manufacturing industry, three commonly used capability indices are the Process Capability Index (*Cp*), the Process Capability Index with Centering (*Cpk*), and the Process Capability Index with Target (*Cpm*). *Cp* measures whether process variability is within specification limits. *Cpk* considers both process variability and the alignment of the process mean with the specification center. *Cpm* is a variant of the capability index that incorporates the target value, considering process variability, centering, and the target. These indices provide numerical measures to determine if a manufacturing process meets predefined specification limits. *Cpk* is widely used in manufacturing because it accounts for the centering of the process mean with the specification center, offering a more comprehensive reflection of process quality.(10) Compared with Cpm, *Cpk* is more straightforward to calculate while providing sufficient information to evaluate process capability. In the manufacturing industry, *Cpk* is the most commonly used process capability index(11–15) because it balances variability and centering, making it a practical and effective metric.(4,16,17) Therefore, in this study, we employed *Cpk* as the metric for assessing process capability.

When product specifications approach the upper specification limit (USL) or lower specification limit (LSL), the risk of producing defective products significantly increases. This is due to process variation and fluctuations that make it more likely for products to fall outside the specification range. Assuming that the probability of process variation and fluctuations follows a normal distribution, the process mean should ideally be positioned at the center of the specification range. In this case, products can remain within specification limits even with some variation. However, when the process is close to the specification boundaries, any small variation, such as minor environmental changes, equipment wear, or operational errors—can cause products to exceed the specifications, resulting in defects. Over time, these risks accumulate, significantly impacting product quality and production efficiency. Therefore, monitoring process variation and adjusting the process means moving away from the specification boundaries are essential strategies to reduce the risk of defective products and ensure consistency and stability in product quality.

In this study, we used a lock manufacturing company as a case study. The company's quality assurance personnel collect one sample from the production line each morning and afternoon to check whether the products meet the customer's specified requirements. However, no further scientific quality control measures are implemented. Consequently, even if the products meet the specified requirements, there is a high risk of the product specifications nearing the upper or lower specification limits, leading to a high probability of producing nonconforming products. Therefore, we aimed to introduce the concept of process capability indices into the factory's quality control practices. Specifically, the objectives of this study are (1) to quantify and improve the process capability of lock products based on *Cpk* and (2) to measure and assess the stability of product quality after equipment maintenance using *Cpk*.

2. Data, Materials, and Methods

2.1 Target company

Established in 2013, the case company specializes in manufacturing locks and components and import-export business. It provides customers with various lock parts and components and is dedicated to developing a range of lock products. The company has a total capital of NTD 10 million and an annual turnover of approximately NTD 100 million. Its factory is located in the Pingtung City Industrial Zone in Taiwan. The company's business scope covers the Americas, Asia, and China. Figure 1 shows the CNC digital lathe used for product manufacturing, where engineers utilize software programs through the control panel to set machining parameters. Sensors are employed to control the cutting tools, ensuring that the dimensions meet the customer's specifications.

(a) (b)

Fig. 1. (Color online) Control panel (a) and machine enclosure (b) of a CNC digital lathe.

2.2 Measurement objectives and methods

We selected a lock case product made of brass from the company, processed using a CNC lathe. Owing to the numerous dimensional specifications within a single product, we focused on the dimension with minimal tolerance (dimension: 3.51 ± 0.038 mm) as the measurement target. The product measurement instrument used is an image-measuring instrument, and all measurements are recorded in millimeters (mm). For the first experiment, the measurement target's *USL* is 3.548 mm, the *LSL* is 3.472 mm, and the center line (*CL*) is 3.51 mm.

During the experiment, the image-measuring instrument was initially operated manually by quality assurance personnel for dimensional measurements. An automated image-measuring instrument was introduced (Fig. 2) to improve measurement efficiency and accuracy. This instrument integrates multiple sensors to perform various functions, including automatic dimensional measurements to make the material inspections more accurate. Once the parameters are set and saved during the first measurement, subsequent measurements of products with the same specifications can be performed automatically by placing them on the measurement platform, with the instrument automatically measuring the predefined dimensions. In summary, the measurement method involves the quality assurance personnel at the company taking one sample each morning and afternoon during the production of the lock case. They measure the target dimension (i.e., the dimension with the minimal tolerance) and record the results.

2.3 Equations

We employed *Cpk* as the quantitative indicator of process capability. *Cpk* is a critical quantitative method in statistical process control (SPC) used to measure whether a process can produce products that meet quality standards within specified limits. The *Cpk* value reflects the deviation of the process mean from the specification center and the relative magnitude of process variation. *Cpk* is defined as

Fig. 2. (Color online) Automated image measuring instrument.

$$Cpk = \min\left(\frac{USL - \bar{\bar{x}}}{3\sigma}, \frac{\bar{\bar{x}} - LSL}{3\sigma}\right), \tag{1}$$

where $\bar{\bar{x}}$ is the overall mean of the sample data (process mean) and σ is the standard deviation of the sample data (process standard deviation). The physical meaning of *Cpk* is to measure the distance from $\bar{\bar{x}}$ to the nearest specification limit, reflecting whether the process mean deviates from the target specification. The *Cpk* formula uses three standard deviations as the denominator to measure the extent of process variation. According to the Production Parts Approval Process (PPAP),[18] the grading of *Cpk* is as follows: $Cpk \geq 1.33$: the process capability is good and the process can stably produce products within specifications; $1.00 \leq Cpk < 1.33$: the process capability is moderate and requires continuous monitoring and improvement; $Cpk < 1.00$: the process capability is insufficient, the product quality is unstable, and an immediate process improvement is necessary. Several studies have utilized *Cpk* as their quality assurance parameter in the field of pharmaceuticals and in decision-making procedures.[12,19,20]

In practical quality control processes, the *x*-bar chart ($\bar{x}$-chart) and range control chart (*R*-chart) are used to visualize the results of sample measurements.[21] For example, as shown in Fig. 2, the $\bar{x}$-chart displays the variation in the twice-daily specification measurements' average, indicating whether the manufacturing process quality is stable. The *R*-chart shows the range (*R*) of the twice-daily specification measurements, illustrating the variation in the daily sampled specification measurements. The $\bar{x}$-chart includes *UCL* and *LCL*, defined as

$$UCL = \bar{\bar{x}} + 3\sigma, \tag{2}$$

$$LCL = \bar{\bar{x}} - 3\sigma. \tag{3}$$

This statistical limit is used to monitor process variation. If a data point exceeds this limit, the process variation is beyond the acceptable range, necessitating investigation and improvement.

In the R-chart, $UCLR$ represents the upper control limit for range, calculated as

$$UCLR = D4 \cdot \overline{R}\,, \tag{4}$$

where $\overline{R}$ is the average of the sample ranges and $D4$ is a constant related to the sample size provided by standard SPC tables.[22]

2.4 Experiment design

The objectives of the first experiment in this study are to quantify the process capability of manufacturing a specific lock case product using *Cpk* and to achieve an increase in *Cpk* by adjusting the lathe parameters. The process is indicated in Fig. 3.

The second experiment in this study aims to measure the process capability after equipment maintenance based on *Cpk*. The same product is used, and three critical dimensions with smaller tolerance values are selected. The product part number is 10-1194-2211, with dimensions of 5.842 ± 0.05, 39.472 ± 0.05, and 35.622 ± 0.05 mm. Measurements for these three dimensions are taken once each morning and afternoon for 20 consecutive days. The data are presented in Appendices 1, 2, and 3. Subsequently, *Cpk* values are calculated to determine the stability of the equipment's machining dimensions.

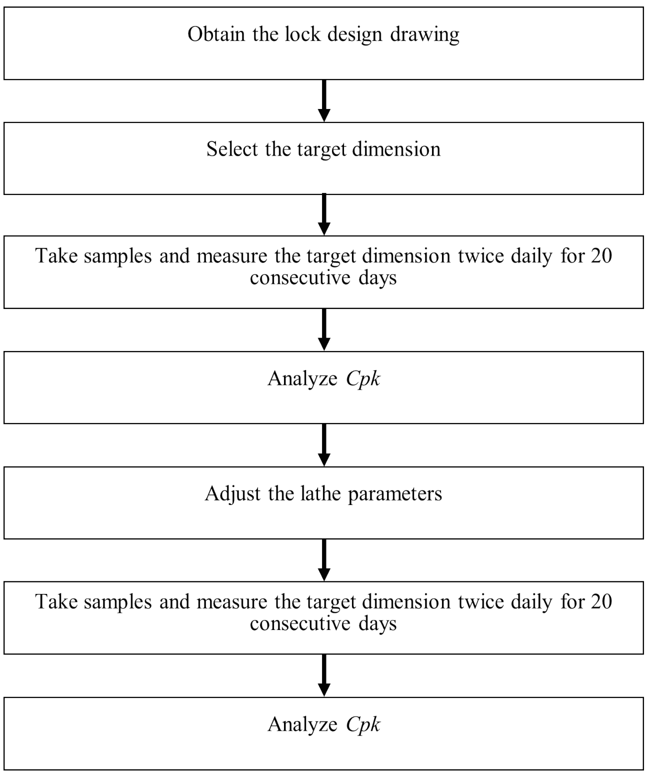

Fig. 3. Process flow for quantifying and improving manufacturing process capability based on *Cpk*.

3. Results

3.1 Quantifying and improving manufacturing process capability based on *Cpk*

To measure the process capability of the target lock product, personnel measure the same critical dimension of the same product each morning and afternoon for 20 consecutive days. Measurements are recorded in millimeters (mm). The $\bar{x}$-chart and *R*-chart are shown in Fig. 4, and the measurement data is presented in Appendix 1. Subsequently, researchers calculated *Cpk* for manufacturing the product as 0.72 (Table 1), below the standard value of 1.33 from the literature. This indicates a risk of producing defective products, necessitating appropriate improvement measures.

To improve the *Cpk* value, engineers adjusted the CNC lathe tool control software to fine-tune the tool's positioning (up, down, left, right) while monitoring the critical dimensions of the

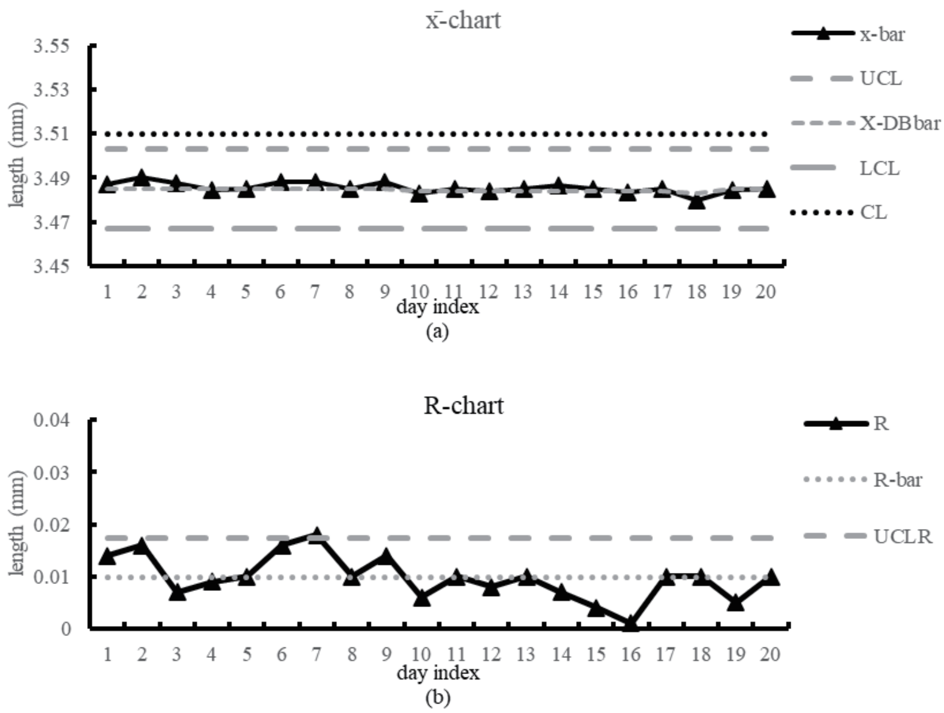

Fig. 4. $\bar{x}$-chart (a) and *R*-chart (b) before improvement. *UCL*: upper control limit, *LCL*: lower control limit, $\bar{x}$ (*x*-bar): average of two daily sample measurements, *R*: difference between the two daily sample measurements, $\bar{R}$ (*R*-bar): average of *R* values over the measurement period, and *UCLR*: upper control limit for range.

Table 1
Differences in *Cpk*, $\bar{\bar{x}}$, and σ before and after improvement.

Measurement timing	*Cpk*	$\bar{\bar{x}}$(mm)	σ
Before improvement	0.72	3.49	0.006
After improvement	1.54	3.51	0.008

product. The $\bar{x}$ value was adjusted to near the specification center line (3.51 mm). A second round of 20-day measurements was then conducted. The results of the retest are shown in Fig. 5.

The $\bar{x}$-chart in Fig. 5 shows that the $\bar{x}$ values are near the specification center line. The calculated *Cpk* value is 1.54 (Table 1), more significant than 1.33, indicating sufficient process capability and no concern for producing nonconforming products. Therefore, it can be concluded that the process is under statistical control, indicating that the process is stable over time.

3.2 Application of *Cpk*: Quantifying post-maintenance production stability

In addition to using *Cpk* to quantify and enhance the process capability of online products, we also aimed to verify whether the process capability reaches an optimal state post-maintenance using *Cpk*. Therefore, three critical dimensions were selected for measurement and data analysis for a recently serviced CNC machine producing the same lock case product as in Experiment 1.

The $\bar{x}$-chart in Fig. 6 shows that the $\bar{x}$ values are near the specification center line, and the *Cpk* value is 1.63, greater than 1.33. This indicates that the process capability is sufficient, and there is no concern for producing nonconforming products. Therefore, it can be concluded that the process is under statistical control, indicating that the process is stable over time.

The $\bar{x}$-chart in Fig. 7 shows that the $\bar{x}$ values are near the specification center line, and the *Cpk* value is 1.53, greater than 1.33. This indicates that the process capability is sufficient, and

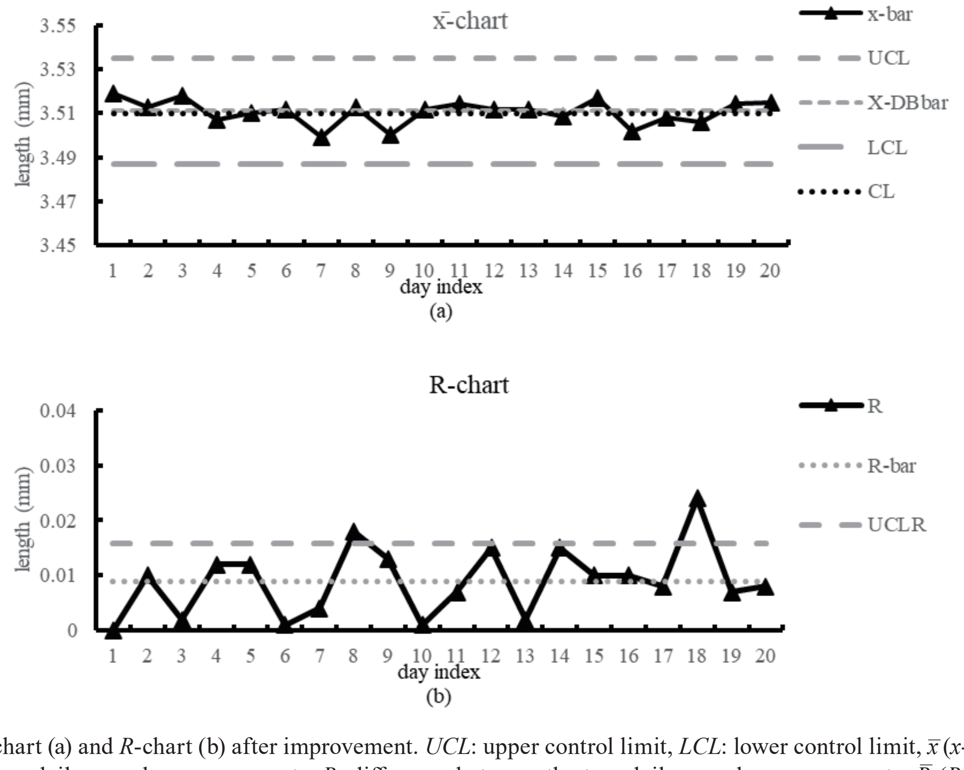

Fig. 5. $\bar{x}$-chart (a) and *R*-chart (b) after improvement. *UCL*: upper control limit, *LCL*: lower control limit, $\bar{x}$ (*x*-bar): average of two daily sample measurements, *R*: difference between the two daily sample measurements, $\bar{R}$ (*R*-bar): average of *R* values over the measurement period, and *UCLR*: upper control limit for range.

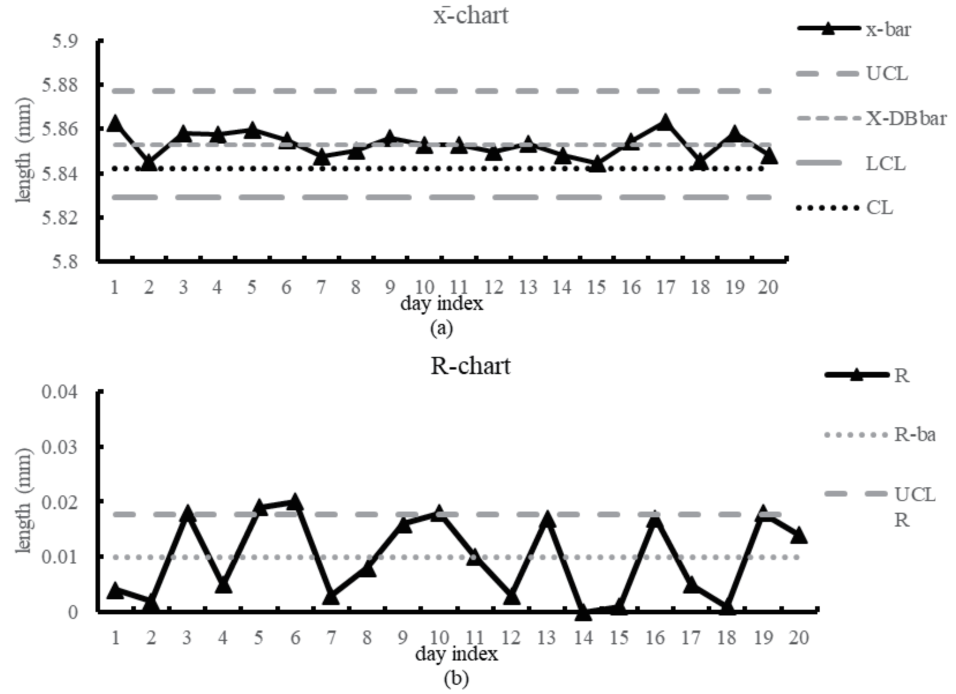

Fig. 6. $\bar{x}$-chart (a) and *R*-chart (b) for the first-dimension data post-maintenance in the case study. *UCL*: upper control limit, *LCL*: lower control limit, $\bar{x}$ (*x*-bar): average of two daily sample measurements, *R*: difference between the two daily sample measurements, $\bar{R}$ (*R*-bar): average of *R* values over the measurement period, and *UCLR*: upper control limit for range.

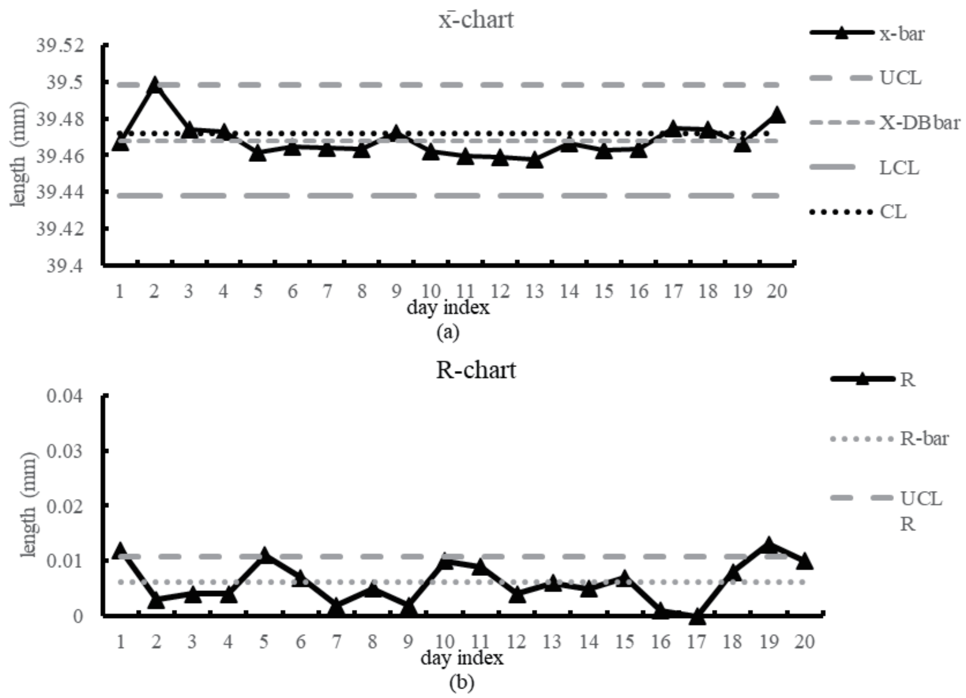

Fig. 7. $\bar{x}$-chart (a) and *R*-chart (b) for the second-dimension data post-maintenance in the case study. *UCL*: upper control limit, *LCL*: lower control limit, $\bar{x}$ (*x*-bar): average of two daily sample measurements, *R*: difference between the two daily sample measurements, $\bar{R}$ (*R*-bar): average of *R* values over the measurement period, and *UCLR*: upper control limit for range.

there is no concern for producing nonconforming products. Therefore, it can be concluded that the process is under statistical control, indicating that the process is stable over time.

The $\bar{x}$-chart in Fig. 8 shows that the $\bar{x}$ values are near the specification center line, and the *Cpk* value is 1.96, greater than 1.33. This indicates that the process capability is sufficient, and there is no concern for producing nonconforming products. Therefore, it can be concluded that the process is under statistical control, indicating that the process is stable over time.

Figures 6–8 show that after the maintenance of the processing equipment, the process capability was analyzed using *Cpk* for three critical dimensions. The *Cpk* values are all greater than 1.33, confirming that the post-maintenance process capability is satisfactory.

4. Discussion

4.1 Theoretical implications of this study

The relationship between "precision processes and stable quality" and *Cpk* is of significant theoretical and practical importance, primarily involving how precise process control can achieve consistent and high-quality product output. This relationship revolves around several core concepts.(23,24) "Precision processes and stable quality" emphasize implementing strict process control during production to ensure that each batch meets predetermined quality

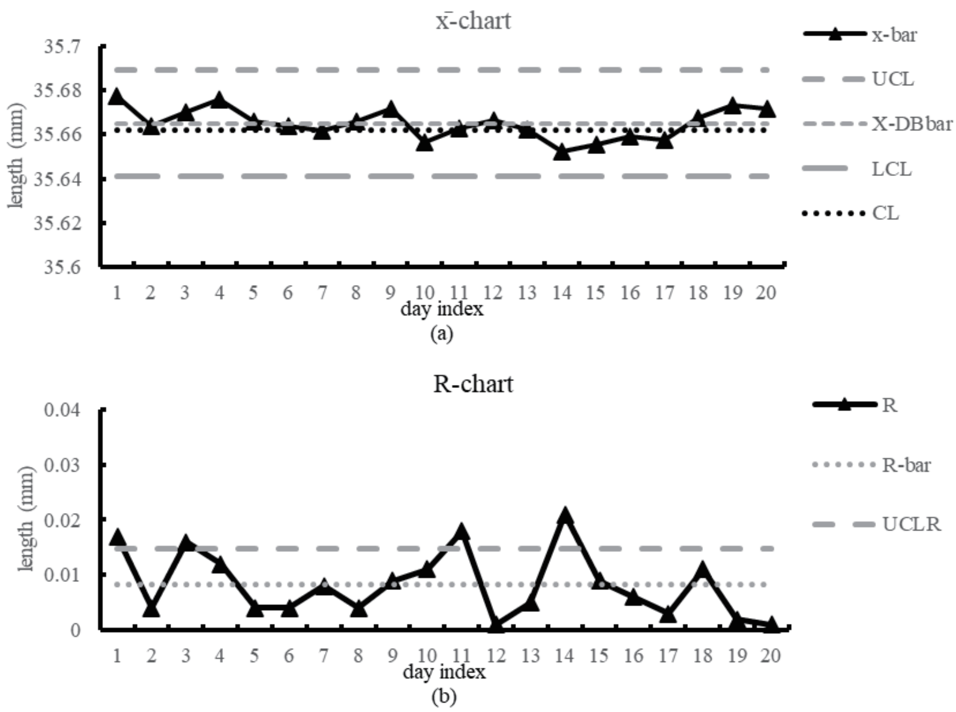

Fig. 8. $\bar{x}$-chart (a) and *R*-chart (b) for the third-dimension data post-maintenance in the case study. *UCL*: upper control limit, *LCL*: lower control limit , $\bar{x}$ (*x*-bar): average of two daily sample measurements, *R*: difference between the two daily sample measurements, $\bar{R}$ (*R*-bar): average of *R* values over the measurement period, and *UCLR*: upper control limit for range.

standards. *Cpk*, as a measurement tool, provides a quantitative way to assess process performance, indicating the alignment of product quality with specification limits. The *Cpk* value, a process capability index, measures whether the output can reliably produce products that meet standards within specified limits. The *Cpk* calculation considers the process mean, variance, and distance to specification limits. A high *Cpk* value, typically greater than 1.33, indicates that the process mean is centered within the specification limits and that process variability is low, resulting in stable product quality. Under the "precision processes and stable quality" strategy, applying *Cpk* can guide process improvement efforts, ensuring that adjustments precisely achieve the goal of enhancing quality. This involves selecting appropriate machinery, equipment, raw materials, working methods, and continuous process monitoring and optimization. Utilizing *Cpk* and other process capability indices for data analysis helps manufacturers identify quality issues, predict potential process failures, and develop countermeasures. This data-driven approach enhances the objectivity and effectiveness of decision-making. In many high-specification manufacturing industries, such as medical devices, automotive, or aerospace, high *Cpk* values are part of compliance requirements and quality control standards. Through precision processes and the application of *Cpk*, companies can effectively reduce the risk of product failure, enhancing confidence among consumers and regulatory bodies. In summary, the relationship between "precision processes and stable quality" and *Cpk* guides the manufacturing industry in achieving continuous product quality optimization and maximizing process efficiency through scientific data analysis and process control techniques.

4.2 Practical implications of this study

In this study, process capability analysis was conducted to eliminate quality issues in turning operations (digital CNC). In addition to controlling product specifications, process capability indices (*Cpk*) were used to manage potential risks of defective products. A *Cpk* value of $\geq$1.33 for digital CNC equipment maintenance was used to verify adequate process capability and ensure post-maintenance dimensional stability. Several recommendations were made to address observed quality issues. Errors exceeding tolerance limits were eliminated, reducing process variability and costs associated with low-quality production. The underlying implications of the study is that *Cpk* reflects the stability of product quality after equipment maintenance, as it captures both the process mean (μ) and variation (σ) within acceptable limits. The *Cpk* formula assesses process capability by comparing the distance between the process mean and the specification limits (i.e., *USL* and *LSL*), then dividing this distance by three standard deviations. The use of three standard deviations is based on the statistical principle that 99.73% of data points in a normal distribution fall within $\pm 3\sigma$, meaning that if the process variation is within this range, most products will meet specifications. Therefore, by calculating *Cpk* after equipment maintenance, it is possible to verify whether the process mean has returned to the center and whether the equipment has effectively reduced variation, ensuring consistent product quality. A higher *Cpk* value indicates a more stable process and consistent product quality post-maintenance, with less variation. Conversely, a lower *Cpk* value may suggest that the process remains unstable after maintenance, with greater quality fluctuations, necessitating further equipment inspection. Thus, in this study, we not only take *Cpk* as a tool for quality control but also as a metric for evaluating the effectiveness of equipment repairs and long-term process stability.

In the CNC production process, sensors are used to differentiate between conforming and nonconforming products, automatically sorting them to prevent mixing and avoid issues during shipment. In terms of measurement, manual operations have been replaced by automated image-measuring instruments, which utilize multiple sensors to perform various functions, including automatic dimensional measurement. This transition has improved measurement efficiency and accuracy while achieving the goal of cost reduction.

Advanced process control techniques such as SPC and automated monitoring systems monitor manufacturing processes in real time, ensuring that process parameters remain within predetermined ranges. Data collection and the application of data analysis and machine learning techniques predict process deviations and optimize them, enhancing product consistency and reducing waste. Comprehensive quality management systems systematically manage quality, including quality plans, objectives, manuals, and operating procedures. Continuous process improvement and technological innovation enhance process efficiency and product quality, addressing market and technological changes. These practices help manufacturing enterprises improve product quality and market competitiveness, reduce production costs, and increase customer satisfaction. Thus, this research is significant for high-tech industries, pharmaceuticals, and automotive manufacturing.

5. Conclusions

Research on “precision processes and stable quality” can be deepened and expanded in various aspects. Future research should focus on integrating intelligent manufacturing systems by combining *Cpk* process capability with IoT, AI, and machine learning technologies to achieve precision processes and stable quality control and reduce unnecessary waste. This includes studying methods for automatically collecting and analyzing process data to adjust parameters in real time. Additionally, process capability analysis should consider the environmental impact of manufacturing processes, exploring ways to minimize energy consumption and waste generation. Developing sustainable process technologies enhances process efficiency, meets environmental standards, and aligns with ESG initiatives. Furthermore, we should investigate achieving personalized production while maintaining high quality and stability. This involves exploring the application of modular design and flexible manufacturing systems to meet diverse market demands, combined with process capability analysis, to achieve the goal of “precision processes and stable quality.” These suggestions can help researchers find new directions and deepen existing research, further advancing technological progress and industrial upgrading in the manufacturing sector.

References

1 M. M. Rounaghi, H. Jarrar, and L.-P. Dana: Future Bus. J. **7** (2021). https://doi.org/10.1186/s43093-021-00079-4
2 J. A. Donovan and F. P. Maresca: Juran's Quality Handbook, J. M. Juran, and A. B. Godfrey, Eds. (The McGraw-Hill Companies, Inc., USA, 1999) 5th ed., Chap. 21.
3 T. Pyzdek: The Six Sigma Handbook: a complete guide for green belts, black belts, and managers at all levels (The McGraw-Hill Companies, Inc., USA 2003) 213.
4 D. C. Montgomery: Introduction to Statistical Quality Control (John Wiley & Sons, Hoboken, NJ, 2019) 8th ed., Chap. 8.
5 B. Bergman: IIE Trans. **41** (2008) 86. https://doi.org/10.1080/07408170802322713
6 A. Koetsier, S. N. van der Veer, K. J. Jager, N. Peek, and N. F. de Keizer: Methods Inf. Med. **51** (2012) 189. https://doi.org/10.3414/ME11-01-0055
7 K. A. Olu-lawal, O. K. Olajiga, A. K. Adeleke, E. C. Ani, and D. J. P. Montero: Int. J. Appl. Res. Social Sci. **6** (2024) 279. https://doi.org/10.51594/ijarss.v6i3.886
8 W.-C. Lee, H.-C. Cheng, and C.-C. Wei: Sens. Mater. **31** (2019) 3575. http://dx.doi.org/10.18494/SAM.2019.2501
9 Y.-M. Cheng and M.-S. Lin: Sens. Mater. **32** (2020) 4201. https://doi.org/10.18494/SAM.2020.3099
10 R. Lin, Y. Yin, J. Chen, and S. Wei: Sens Mater. **31** (2019) 3559. https://doi.org/10.18494/SAM.2019.2509
11 K.-S. Chen, K.-J. Wang, and T.-C. Chang: Int. J. Prod. Res. **55** (2017) 4963. https://doi.org/10.1080/00207543.2017.1282644
12 D. de-Felipe and E. Benedito: Int. J. Adv. Manuf. Technol. **92** (2017) 1687. https://doi.org/10.1007/s00170-017-0273-6
13 S. Koppel and S. I. Chang: Procedia Manuf. **5** (2016) 122. https://doi.org/10.1016/j.promfg.2016.08.012
14 Y. Yang: Recent Dev. Mech. Intell. Robot. **415** (2019) 415. https://doi.org/10.1007/978-3-030-00214-5_53
15 W. L. Pearn and P. Lin: Comput. Ind. Eng. **47** (2004) 351. https://doi.org/10.1016/j.cie.2003.03.001
16 W. L. Pearn, S. Kotz, and N. L. Johnson: J. Qual. Technol. **24** (1992) 216. https://doi.org/10.1080/00224065.1992.11979403
17 K. Chen, M. Huang, and R.-K. Li: Int. J. Prod. Res. **39** (2001) 4077. https://doi.org/10.1080/00207540110073082
18 PPAP Documents: https://ppapdocuments.com/ (accessed 30 June 2022).
19 A. P. K. Mahapatra, J. Song, Z. Shao, T. Dong, Z. Gong, B. Paul, and I. Padhy: J. Drug Delivery Ther. **10** (2020) 333. https://jddtonline.info/index.php/jddt/article/view/4288
20 W. Pearn and K. Chen: Qual. Reliab. Eng. Int. **15** (1999) 321. https://doi.org/10.1002/(SICI)1099-1638(199907/08)15:4<321::AID-QRE258>3.0.CO;2-5
21 K. Palmer and K.-L. Tsui: Ann. Oper. Res. **87** (1999) 31. https://doi.org/10.1023/A:1018993221702
22 L. K. Chan and H. J. Cui: Nav. Res. Logist. **50** (2003) 555. https://doi.org/10.1002/nav.10077
23 A. Pfadt and D. J. Wheeler: J. Appl. Behav. Anal. **28** (1995) 349. https://doi.org/10.1901/jaba.1995.28-349
24 S. Kotz and N. L. Johnson: J. Qual. Technol. **34** (2002) 2. https://doi.org/10.1080/00224065.2002.11980119

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Appendix

Appendix 1

day index	data 1 (mm)	data 2 (mm)	*X*-bar (mm)	*R* (mm)
1	3.494	3.48	3.487	0.014
2	3.498	3.482	3.49	0.016
3	3.484	3.491	3.4875	0.007
4	3.489	3.48	3.4845	0.009
5	3.49	3.48	3.485	0.01
6	3.496	3.48	3.488	0.016
7	3.497	3.479	3.488	0.018
8	3.48	3.49	3.485	0.01
9	3.481	3.495	3.488	0.014
10	3.486	3.48	3.483	0.006
11	3.49	3.48	3.485	0.01
12	3.488	3.48	3.484	0.008
13	3.48	3.49	3.485	0.01
14	3.483	3.49	3.4865	0.007
15	3.487	3.483	3.485	0.004
16	3.484	3.483	3.4835	0.001
17	3.48	3.49	3.485	0.01
18	3.485	3.475	3.48	0.01
19	3.487	3.482	3.4845	0.005
20	3.48	3.49	3.485	0.01

USL = 3.548, LSL = 3.472, CL = 3.51, σ = 0.006, and Cpk = 0.722
USL: Upper Specification Limit, LS: Lower Specification Limit, CL: Center Line, and σ: sample standard deviation.

Appendix 2

day index	data 1 (mm)	data 2 (mm)	*X*-bar (mm)	*R* (mm)
1	3.519	3.519	3.519	0
2	3.508	3.518	3.513	0.01
3	3.517	3.519	3.518	0.002
4	3.501	3.513	3.507	0.012
5	3.504	3.516	3.51	0.012
6	3.511	3.512	3.5115	0.001
7	3.501	3.497	3.499	0.004
8	3.522	3.504	3.513	0.018
9	3.507	3.494	3.5005	0.013
10	3.512	3.511	3.5115	0.001
11	3.518	3.511	3.5145	0.007
12	3.519	3.504	3.5115	0.015
13	3.513	3.511	3.512	0.002
14	3.516	3.501	3.5085	0.015
15	3.512	3.522	3.517	0.01
16	3.497	3.507	3.502	0.01
17	3.504	3.512	3.508	0.008
18	3.494	3.518	3.506	0.024
19	3.511	3.518	3.5145	0.007
20	3.511	3.519	3.515	0.008

Appendix 3

day index	data 1 (mm)	data 2 (mm)	*X*-bar (mm)	*R* (mm)
1	5.861	5.865	5.863	0.004
2	5.844	5.846	5.845	0.002
3	5.849	5.867	5.858	0.018
4	5.855	5.86	5.8575	0.005
5	5.85	5.869	5.8595	0.019
6	5.845	5.865	5.855	0.02
7	5.849	5.846	5.8475	0.003
8	5.854	5.846	5.85	0.008
9	5.864	5.848	5.856	0.016
10	5.862	5.844	5.853	0.018
11	5.848	5.858	5.853	0.01
12	5.851	5.848	5.8495	0.003
13	5.862	5.845	5.8535	0.017
14	5.848	5.848	5.848	0
15	5.844	5.845	5.8445	0.001
16	5.846	5.863	5.8545	0.017
17	5.866	5.861	5.8635	0.005
18	5.845	5.846	5.8455	0.001
19	5.867	5.849	5.858	0.018
20	5.855	5.841	5.848	0.014

Appendix 4

day index	data 1 (mm)	data 2 (mm)	*X*-bar (mm)	*R* (mm)
1	39.473	39.461	39.467	0.012
2	39.5	39.497	39.4985	0.003
3	39.476	39.472	39.474	0.004
4	39.475	39.471	39.473	0.004
5	39.467	39.456	39.4615	0.011
6	39.461	39.468	39.4645	0.007
7	39.465	39.463	39.464	0.002
8	39.466	39.461	39.4635	0.005
9	39.473	39.471	39.472	0.002
10	39.457	39.467	39.462	0.01
11	39.455	39.464	39.4595	0.009
12	39.461	39.457	39.459	0.004
13	39.455	39.461	39.458	0.006
14	39.469	39.464	39.4665	0.005
15	39.459	39.466	39.4625	0.007
16	39.464	39.463	39.4635	0.001
17	39.475	39.475	39.475	0
18	39.478	39.47	39.474	0.008
19	39.473	39.46	39.4665	0.013
20	39.487	39.477	39.482	0.01

Appendix 5

day index	data 1 (mm)	data 2 (mm)	*X*-bar (mm)	*R* (mm)
1	35.669	35.686	35.6775	0.017
2	35.662	35.666	35.664	0.004
3	35.678	35.662	35.67	0.016
4	35.67	35.682	35.676	0.012
5	35.664	35.668	35.666	0.004
6	35.662	35.666	35.664	0.004
7	35.666	35.658	35.662	0.008
8	35.668	35.664	35.666	0.004
9	35.676	35.667	35.6715	0.009
10	35.662	35.651	35.6565	0.011
11	35.654	35.672	35.663	0.018
12	35.666	35.667	35.6665	0.001
13	35.66	35.665	35.6625	0.005
14	35.663	35.642	35.6525	0.021
15	35.651	35.66	35.6555	0.009
16	35.656	35.662	35.659	0.006
17	35.659	35.656	35.6575	0.003
18	35.673	35.662	35.6675	0.011
19	35.674	35.672	35.673	0.002
20	35.671	35.672	35.6715	0.001

USL = 35.712, LSL = 35.612, CL = 35.662, and σ = 0.008