

2024

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Recommended Citation

Sedeek, Mostafa Awadalla; Elerian, Fatma Abdallah; Abouelatta, Ossama Badie; and AbouEleaz, Mona. A. (2024) "A Decision-making Approach to Reduce the Risk of Measurement Uncertainty for Product Size," *Mansoura Engineering Journal*: Vol. 49 : Iss. 5 , Article 2.
Available at: <https://doi.org/10.58491/2735-4202.3223>

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ORIGINAL STUDY

A Decision-making Approach to Reduce the Risk of Measurement Uncertainty for Product Size

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Abstract

The measurement uncertainty has a significant impact on quality control processes. This is particularly true of standards that are assessed to determine if a product is compliant. This ambiguity introduces two potential risks of decision-making: accepting a nonconventional product (the consumer's risk) or rejecting a conventional product (the producer's risk). This investigation explores the potential for false decisions caused by measurement errors in product assessments. By studying data near the control limits, a greater understanding of the manufacturing process is intended to facilitate informed decision-making and guide the implementation of effective quality control methods. The investigation highlights the importance of selecting suitable measurement instruments to reduce false positive quality control decisions, which resulted in 11.43% of initially accurate parts violating the 0.1 mm tool. The 0.001 mm tool has a higher degree of precision than the 0.01 mm tool, but it may not always be practical financially.

Keywords: Decision-making, Risk, Size tolerance, Uncertainty

1. Introduction

Manufacturing thrives on quality control, ensuring products meet specific requirements. Achieving this objective depends on accurate measurements, yet inherent uncertainties lurk within the process. Gauge measurement errors exemplify this risk, potentially misclassifying good parts as defective and vice versa, leading to costly consequences for producers and buyers (Vives et al., 2023). This underscores the crucial role of understanding and managing uncertainty in decision-making throughout the manufacturing lifecycle. Zero defect manufacturing, is the epitome of research's constant pursuit of perfection. However, even with cutting-edge technologies for defect detection and correction, uncertainty persists. This necessitates innovative solutions like the data-driven and knowledge-based decision support system presented (Psarommatis and Kiritsis, 2022). Its effectiveness

in real-world scenarios like computer chip manufacturing underscores the importance of tackling uncertainty to enhance quality control and production efficiency. Dimensional accuracy is very critical in mechanical parts, demanding robust inspection methods. This study introduces a sensor-based decision support system capable of real-time detection and corrective action for dimensional defects. By minimizing the impact of such flaws on production time and cost, this approach highlights the significance of managing uncertainty in dimensional measurements. Radiography computed tomography holds immense promise for complex part inspection, but uncertainty in its measurements hinders widespread adoption (Lifton, 2023). The study bridges this gap by proposing a novel method for quantifying uncertainty arising from voxel size, a key contributor. This advancement empowers manufacturers with confidence in product quality and reduces uncertainty, demonstrating the value of addressing

Received 13 March 2024; revised 28 May 2024; accepted 2 June 2024.
Available online 16 July 2024

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<https://doi.org/10.58491/2735-4202.3223>

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uncertainty in dimensional measurements using radiography computed tomography.

Similar challenges face the three-probe method for roundness measurement, particularly in its susceptibility to uncertainty (Shi et al., 2021). This research combats this limitation by presenting a novel method for uncertainty evaluation and reduction, demonstrably improving accuracy and reliability. Its contribution exemplifies the importance of managing uncertainty in mechanical part inspection for enhanced quality control. Machine tool stiffness directly impacts the accuracy and quality of machined parts (Majda et al., 2021). This study tackles this challenge by introducing a novel method for measuring both translational and torsional stiffness, crucial parameters for quality assurance. By empowering manufacturers to identify and address potential stiffness-related issues, this research underscores the critical role of managing uncertainty in machine tool performance. The subsequent literature delves deeper into various aspects of uncertainty in decision-making, particularly within the realm of conformity assessment (Pendril, 2006, 2014; Wu, 2013).

Accurate measurement plays a critical role in various processes, particularly within quality control settings. Even minor uncertainties in measurement data can lead to erroneous decisions, impacting product quality, resource allocation, and consumer trust. The interplay between measurement uncertainty and decision-making through an examination of relevant research across diverse disciplines is explored. Studies focused on specific manufacturing processes exemplify the critical role of precise measurements. Research on in-situ monitoring and control systems in metal-based laser additive manufacturing (He et al., 2022), demonstrates that integrating such systems reduces manufacturing errors, ultimately leading to improved product quality and informed decision-making. Similarly, a study examining machining processes highlights the importance of minimizing measurement uncertainty through the use of sophisticated sensors to enhance decision-making during process monitoring (Kandavalli et al., 2023). In addition to specific processes, research in material extrusion additive manufacturing shows how important it is to reduce measurement uncertainty to make sure high-quality products by showing how measurement affects key control parameters (Petousis et al., 2023). Furthermore, a comprehensive review of machine learning techniques in additive manufacturing emphasizes the importance of understanding measurement uncertainty for effective quality control measures (Kumar et al., 2023).

While the studies mentioned above focus on manufacturing processes, the concept of measurement uncertainty extends to supply chain management. Research on blockchain technology in remanufacturing supply chains reveals how measurement uncertainty can impact consumer risk and trust (Niu et al., 2022), highlighting the far-reaching consequences beyond the immediate production environment. The last study, which was about multi-criteria decision-making methods, did not directly talk about measurement uncertainty, but it seems to understand its importance by suggesting a method that might take uncertainty into account (Božani et al., 2022). These studies highlight the need for quantitative or qualitative approaches, encompassing impact measures for informed and objective decision-making, further emphasizing the critical role of addressing uncertainty in various stages of the manufacturing process.

The following will explore the concept of 'fitness for purpose' within general measurements, analyze the costs associated with decision-making errors, and propose methods for accurate process performance measurement amidst uncertainty (Wu, 2013; Pendril, 2006). Additionally, the importance of measurement uncertainty in conformity assessment and impact evaluation was explained, underscoring the need for well-defined specifications and clear decision rules to manage uncertainty and ensure reliable and accurate outcomes (Pendril, 2014; 17000 II, 2004; Committee, 2013; ASMEa; Bell, 2001). This exploration of uncertainty in decision-making, its risks, and various approaches to mitigate it serves as the foundation for the present study, which aims to contribute to a deeper understanding of its impact and develop effective strategies for managing it within the complex world of manufacturing.

2. Theoretical background

2.1. Geometric dimensioning and tolerancing (GD and T)

Geometric Dimensioning and Tolerancing (GD and T) plays a pivotal role in ensuring dimensional accuracy and reliability within manufacturing and quality control processes. This standardized system, governed by International Organization for Standardization (ISO) and industry standards (Adams, 2008; Meirbek et al., 2020; Jcgm, 2008), specifies dimensions and tolerances on engineering drawings while explicitly quantifying measurement uncertainty. This quantification empowers informed and accurate decision-making throughout the manufacturing life-cycle. However, achieving perfect measurements

remains elusive due to inherent uncertainties arising from various factors. These include the measurement process itself, device characteristics, setup repeatability, and workpiece parameters such as form error, surface roughness, and shape (Jalid et al., 2015). Machine repeatability can further contribute to uncertainty, particularly when assessing positioning accuracy. Recognizing and addressing this inherent uncertainty is crucial in GD and T practices. Instrument uncertainty stemming from the measuring tool's calibration accuracy and resolution demands consideration. Operator skill and experience also play a role, introducing operator uncertainty. Additionally, environmental factors like temperature, humidity, and vibration contribute to environmental uncertainty. Understanding and managing the combined effect of these individual uncertainties, known as total uncertainty, becomes paramount for accurately interpreting GD and T measurements and making informed decisions about product conformance to specified tolerances. Recent years have witnessed a surge in efforts to minimize uncertainty in GD and T measurements, driven by compelling advantages (Shi et al., 2021; Rachakonda et al., 2019). Firstly, reduced uncertainty translates to improved product quality as manufacturers gain greater confidence in their products meeting specified tolerances. Secondly, it translates to cost savings by minimizing scrap parts and rework, leading to resource optimization for manufacturers. Ultimately, minimizing uncertainty in GD and T measurements empowers manufacturers to deliver products that consistently meet or exceed customer expectations, fostering stronger customer relationships and a competitive edge.

2.2. Decision rules

Within the realm of product quality assessment, decision rules serve as indispensable tools for achieving compliant outcomes. These structured frameworks enable informed decision-making and mitigate the risk of errors (Ellison and Williams, 2007). Essentially, a decision rule establishes two key regions: the acceptance zone and the rejection zone. Products demonstrating compliant characteristics reside within the former, while noncompliant products occupy the latter, also known as acceptance limits. The specified decision rule, often referred to as 'simple acceptance' or 'shared risk,' establishes the specification limit as the acceptance limit (ILAC-G8:09/2019, 2019). This approach simplifies compliance assessment by generating a straightforward 'pass' or 'fail' judgment for various scenarios. While the simple acceptance decision rule offers convenience with its 'pass/fail' judgment,

its limitations become evident when considering measurement uncertainty. Ignoring uncertainty, treating both producer and consumer risks equally, and lacking nuanced outcomes compromise its accuracy and applicability, particularly in critical applications. International Laboratory Accreditation Cooperation Guidelines (guidelines on decision rules and statements of conformity, ILAC-G8:09/2019) provide essential guidance for managing both producer and consumer risk within the manufacturing context. Producer risk denotes the potential for rejecting acceptable products, incurring unnecessary costs. Conversely, consumer risk involves the unintentional acceptance of non-compliant products, posing potential safety and quality concerns (Ellison and Williams, 2007; ILAC-G8:09/2019, 2019). In manufacturing quality control, various decision rules are employed, each with distinct advantages and limitations when dealing with measurement uncertainty. The most basic rule, the Go/No-Go Rule (Simple Acceptance Rule), offers a straightforward 'pass' or 'fail' classification based on a single tolerance limit. While easy to implement, it does not account for measurement uncertainty, potentially leading to high risks of errors. Tolerance intervals address this issue to a limited extent by statistically defining a range within the tolerance limits where conforming parts are expected to fall. However, this approach requires knowledge of the measurement process and statistical analysis. Confidence Intervals share similarities with tolerance intervals but focus on the range where a single conforming part's measurement is likely to fall with a specific level of confidence. While acknowledging uncertainty, confidence intervals might not directly translate into clear 'pass/fail' decisions, requiring additional interpretation.

2.3. Role of uncertainty in decision-making

Critically impacting decision-making in various fields, current approaches to incorporating measurement uncertainty often lack a unified and standardized framework for evaluation and risk management. This absence of harmonization across disciplines generates challenges in achieving consistency and accuracy when quantifying uncertainty, ultimately hindering informed decision-making. While a 'one-size-fits-all' approach to integrating uncertainty remains unreachable, the adoption of clear and standardized methods is fundamental to enhancing reliability and precision in decision-making across various domains. Measurement uncertainty introduces many complications, including inaccurate error estimations and

difficulties in interpreting discrepancies between test results. This inherent variability escalates the risk of erroneous decisions, potentially leading to the rejection of compliant entities or the acceptance of noncompliant ones, especially when these entities reside near tolerance limits. Recognizing and effectively managing measurement uncertainty is therefore crucial for ensuring the reliability and accuracy of decision-making processes.

3. Quantifying uncertainty: a review of existing methods

Previous research has extensively explored the challenges and nuances associated with measurement uncertainty and its impact on decision-making. Notably, a method to diminish producer risk through conducting 'n' additional measurements of a regulated quantity within a designated guard band is proposed (Volodarsky et al., 2020). This approach acknowledges the inherent variability in measurements and seeks to mitigate its influence on producer risk. In addition (Alkhatib et al., 2009), shows a complete model that uses both Monte Carlo and fuzzy logic to figure out how much uncertainty there is caused by random and intentional mistakes in a multidimensional measurement equation. This model helps tell the difference between random and systematic error parts by using probabilistic and fuzzy-random methods. This gives us a more complete picture of where uncertainty comes from. Additionally, the crucial role of incorporating uncertainty when evaluating samples against legal or compositional limitations is emphasized in (Desimoni and Brunetti, 2011). This work underlines the significance of adhering to established guidelines set forth by organizations like the American Society of Mechanical Engineers (ASME) and the International Organization for Standardization, which aim to ensure the accuracy and reliability of measurements within testing and calibration laboratories.

4. Research gap

Current limitations in decision-making based on size measurements necessitate further investigation. While research acknowledges the impact of measurement uncertainty, established procedures for determining the probability of erroneous decisions related to size remain elusive. Bridging this knowledge gap requires a deeper understanding of uncertainty and the development of robust approaches to enhance the reliability and accuracy of size-based decisions within manufacturing and design.

This research aims to optimize size measurement uncertainty, ultimately reducing decision-making risk in these critical domains. By developing a comprehensive framework for managing and minimizing uncertainty, the project seeks to achieve the following objectives.

- (a) Identify and characterize the factors contributing to size measurement uncertainty, along with their influence on decision-making within manufacturing and design processes.
- (b) Evaluate and compare existing methods for managing and reducing size measurement uncertainty, assessing their effectiveness across diverse scenarios.
- (c) Develop and validate novel approaches for optimizing size measurement uncertainty, prioritizing practicality, efficiency, and cost-effectiveness in implementation.
- (d) Quantify the impact of optimized measurement uncertainty on decision-making, encompassing product quality, waste reduction, cost savings, and overall operational efficiency within manufacturing and design contexts.

To achieve these goals, the research will embark on a comprehensive exploration of the current state of size measurement uncertainty within the manufacturing industry. This investigation will encompass the identification of uncertainty sources, their impact on decision-making, and the existing challenges associated with managing them. Existing management and reduction techniques will be rigorously evaluated, paving the way for the development of improved solutions. Ultimately, the research seeks to deliver practical solutions and recommendations for optimizing size measurement uncertainty, empowering manufacturers and designers with the knowledge and tools necessary to make informed decisions that optimize product quality, minimize waste and rework, enhance efficiency, and ensure regulatory compliance. The study will explore size measurement uncertainty in the manufacturing sector, identify sources, evaluate their impact on decision-making, and identify challenges. It aims to improve existing strategies and provide practical solutions for refining uncertainty and enhancing product quality, efficiency, and regulatory compliance.

5. Motivation and contribution

The criticality of size measurement uncertainty in manufacturing cannot be overstated, as it profoundly impacts product quality, functionality, and

cost-effectiveness. Inaccuracies in size measurements can cascade into a multitude of downstream consequences, jeopardizing assembly processes, diminishing product performance, and inflating manufacturing costs due to rework and scrapped materials. Consider, for instance, the production of precision components like gears or bearings, where minute deviations in size significantly affect their functionality. Measurements marred by uncertainty can lead to improper component fitment or performance failures, triggering a domino effect of increased rework, scrap, and production downtime. This translates to higher manufacturing costs and eroded profitability. Furthermore, inaccurate size measurements raise the specter of non-compliance with stringent quality standards and regulations, potentially incurring hefty fines and legal repercussions. Industries like aerospace and medical devices operate under rigorous regulatory frameworks, where non-compliance can trigger product recalls and reputational damage, resulting in severe financial losses. Therefore, the optimization of size measurement uncertainty assumes paramount importance in manufacturing, ensuring products meet specified requirements, minimizing error risk, and curtailing production costs. By effectively managing and reducing measurement uncertainty, manufacturers can achieve enhanced product accuracy and consistency, minimize waste, and bolster operational efficiency. These improvements ultimately lead to increased customer satisfaction, improved profitability, and a distinct competitive edge within the marketplace. Overall, the paper's contribution lies in reinforcing the importance of existing knowledge on measurement uncertainty and demonstrating its practical application through real-world examples. It also bridges the gap between uncertainty and decision-making, encouraging a more comprehensive approach to managing this critical aspect of manufacturing quality control.

6. Framework

Fig. 1 presents a comprehensive flowchart depicting the essential steps involved in the size inspection of a mechanical part. This visual representation outlines the process for quantifying measurement uncertainty, establishing a decision rule, and subsequently evaluating the potential for erroneous decisions (risk analysis). The inspection of mechanical parts for quality control follows a structured approach. After selecting suitable equipment and part preparation, measurements are taken while acknowledging potential uncertainties.

Recorded results are then compared with established decision criteria, based on part specifications, tolerances, and calculated uncertainty. Conformance is determined by these limits, with non-conforming parts undergoing further evaluation. The process recognizes the risk of errors, considering both accepting a bad part and rejecting a good one. If the error risk is unacceptable, adjustments to the decision criteria or additional measures may be implemented to minimize uncertainty and ensure reliable quality control.

The probability of wrong decisions in the context of measurement uncertainty refers to two main types of errors. Consumer Risk: this is the probability of accepting a nonconforming part. In other words, the measurement indicates the part is within tolerance limits, but it falls outside the acceptable range. Producer Risk: this is the probability of rejecting a conforming part. The measurement suggests the part is outside the tolerance limits, but it's actually within the acceptable range.

Establishing an acceptable level of risk in quality control lacks a one-size-fits-all solution. Factors like the error costs (e.g., a critical system failure), industry standards, and the manufacturer's risk tolerance all play a role. Calculated risks are then weighed against these factors. If the risks are deemed too high, manufacturers may choose to employ a more precise measuring tool, adjust tolerance limits, or implement a more complex decision-making process to ensure reliable part quality control.

7. Experimental work

Adherence to the procedures outlined in Fig. 1 necessitates the availability of essential tools and resources. This includes ensuring calibrated, functional measuring devices and appropriate fixtures that facilitate adherence to established protocols. The illustrated flowchart details a meticulous and systematic methodology for inspecting mechanical parts. This method encompasses critical steps such as part cleaning, precise positioning, calibration of measuring equipment (e.g., micrometers or calipers), and verification of instrument functionality. Following the flowchart's guidance, the measurement equipment is prepared, measurements are meticulously taken and recorded, and necessary environmental adjustments are incorporated. Subsequent analysis involves quantifying measurement uncertainty and utilizing statistical or mathematical techniques to estimate potential error margins. These calculations inform decision-

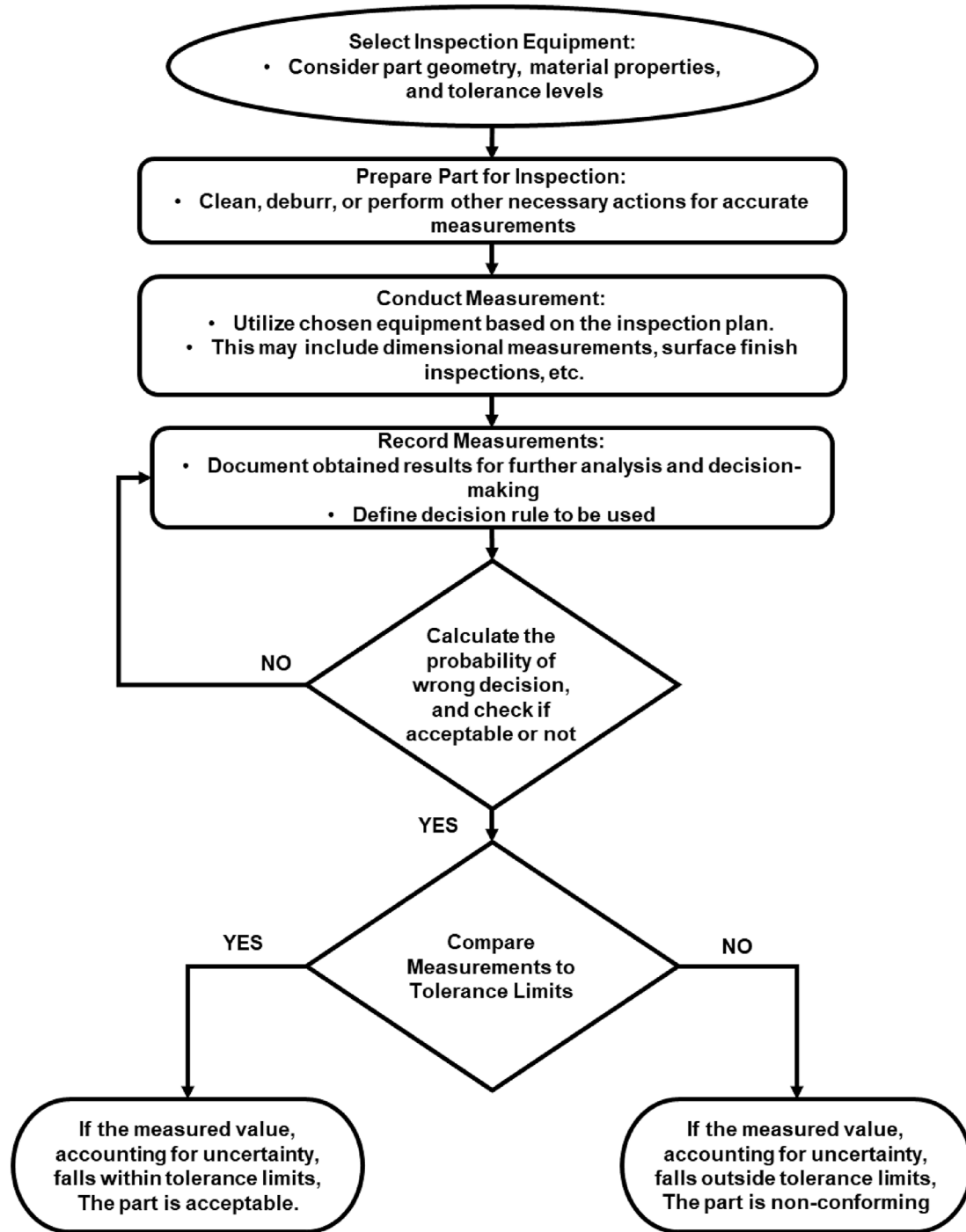


Fig. 1. Mechanical part inspection process.

making processes and highlight potential risks or concerns, ultimately ensuring the inspected part adheres to prescribed requirements. Notably, the entire inspection process, including measurement results, uncertainty calculations, the applied decision rule, and estimated error probability, is meticulously documented for future reference and potential review.

7.1. Sample preparation

The specimens employed in this research consist of seven cylindrical samples made from ST-37 steel. Each sample is 80 mm long, with the initial 20 mm segment having a diameter of 22 mm and the subsequent 60 mm section having a diameter of 18.5 mm. The specimens were machined to have a

lower section with a diameter of 18.50 mm. Therefore, 18.50 mm was adopted as the nominal value from the designer's perspective. This aligns with the concept of the nominal value representing the designed or targeted dimension. These samples are derived from the machining process of a steel cylinder originally measuring 700 mm in length and having a 25 mm diameter. The process involves cutting a 700 mm long bar into 80 mm sections, turning each section to achieve a diameter of 22 mm for the first 20 mm and 19 mm for the remaining 60 mm. The samples are machined using a Victor Vturn Plus 20–2011 CNC turning machine equipped with FANUC's control model (0i-TD), as shown in Fig. 2, reducing the diameter from 19 mm to 18.5 mm for the 60 mm, ensuring high accuracy and consistency in achieving the required specifications. The samples will be prepared in a controlled and systematic manner, ensuring their dimensional accuracy and suitability for the subsequent measurement and analysis in this study.

7.2. Calibration of the measuring tool (micrometer 0.001)

The calibration of a micrometer is crucial for its accuracy and reliability in measuring samples. It follows the established procedures and standards, considering the manufacturer's guidelines and industry standards (Japanese Industrial Standard, and ASME B89.1.13–2013 (JIS; ASMEb)). Here's a step-by-step guide on how to calibrate a micrometer using a reference standard.

- (a) Preparation: gather necessary calibration standards and accessories, such as a gauge block set,



Fig. 2. CNC lathe machine (Victor Vturn Plus 20–2011 model).

thermo-hygrometer, micrometer holder, ethanol, lint-free gloves, or paper. Wear gloves to prevent contamination.

- (b) Pre-calibration checking: inspect the micrometer for missing or defective parts, check the display for clarity and readability, and ensure smooth movement throughout its range.
- (c) Cleaning the micrometer and gauge block: clean the micrometer and gauge block using ethanol and a lint-free cloth or paper. Separate clean gauge blocks from the set to avoid mixing them with unclean blocks.
- (d) Stabilization: stabilize the micrometer and gauge block in a laboratory environment for specific temperatures and relative humidity to minimize thermal expansion effects.
- (e) Calibration procedure: Use a reference standard, such as JIS B-7502, or ASME B89.1.13–2013 (R2022), to calibrate the micrometer.
- (f) Instrumental error: record the initial environmental conditions, zero the micrometer, measure the first calibration point five times, calculate the average, and repeat for the remaining calibration points.
- (g) Parallelism of the measuring face: place a 1 mm gauge block in different locations across the measuring face, record the readings, and calculate the parallelism error.

Fig. 3 displays a graphical representation of the calibration outcomes, providing a visual depiction of the gathered data. The chart exhibits essential parameters and measurements acquired during calibration, offering valuable insights into the calibrated equipment's performance and accuracy. Presented as a line graph, the chart illustrates the deviations in measurements at specific points. As anticipated, deviations increase as measurements move away from the central range (around 12.5 mm) towards the lower and upper boundaries. Consequently, the observed error consistently maintains an impressively narrow margin, remaining within a mere ± 0.002 mm across the entire measurement range. This exceptionally low margin of error strongly supports the micrometer's high quality and reliability in measurements, affirming its status as a precision instrument with commendable accuracy.

A detailed analysis of a digital micrometer model was conducted to evaluate its performance and measurement error, Table 1. The calibration was conducted in a controlled environment, maintaining a stable temperature of 20 ± 2 °C. Temperature considerations were made, and any variations were assumed to follow a normal distribution pattern. It



Fig. 3. Maximum permissible error.

Table 1. Uncertainty budget calculation.

Uncertainty Source	Estimated Limit	Units	Evaluation Method	Probability Distribution	Divisor	Standard Uncertainty
Gauge block tolerance	0.1400	μm	B	Rectangular	1.732	0.081
Calibration uncertainty for gauge block	0.0650	μm	B	Normal	2	0.033
Uncertainty in coefficient of thermal expansion	0.0560	μm	B	Normal	2	0.028
Nominal coefficient of thermal expansion difference	0.1100	μm	B	Normal	2	0.055
Temperature difference	0.1300	μm	B	Normal	2	0.065
Repeatability	0.0005	μm	A	Normal	2.236068	0.000
Combined uncertainty, u						0.124994573
Expanded uncertainty ($K = 2$, 95% confidence), U						0.250

was determined that the expected temperature difference between the gauge and micrometer blocks was under 0.5°C .

An uncertainty budget is crucial for precise measurement and quality control, highlighting sources of uncertainty impacting the process. The estimated limit, units of measurement, evaluation method, probability distribution, divisor, and standard uncertainty are some of the things that are shown in this table that affect measurement uncertainty. The methodology to calculate each component of the uncertainty is as follows.

7.2.1. Gauge block tolerance

The blocks utilized in our study were confirmed to fall within the tolerance limits specified for a grade 0 set. Within this grade 0 set, the blocks had the potential to deviate within a range of $-0.14\ \mu\text{m}$ to $+0.14\ \mu\text{m}$ from their nominal values. To account for

this uncertainty, a rectangular distribution was assumed.

7.2.2. Calibration uncertainty for gauge block

This value for calibration uncertainty is obtained directly from the calibration certificate of the gauge block set that was used in the study. It represents a critical piece of information in assessing the overall uncertainty of the micrometer calibration process.

7.2.3. Uncertainty in coefficient of thermal expansion (CTE)

The standard reference temperature for the length of a gauge block is typically set at 20°C . Yet, achieving precise calibration of a micrometer at exactly 20°C is frequently unfeasible, leading to potential uncertainties in the measurement procedure. If temperature correction is not applied, the resulting uncertainty arising from the micrometer

and gauge blocks not being at 20 °C can be estimated using the following equation:

$$\Delta L = L\Delta\alpha(20 - T)$$

where,

L = the nominal length

T = the temperature

$\Delta\alpha$ = the difference in the coefficient of thermal expansion between the gage blocks and the micrometer

The variation in the coefficient of thermal expansion between the gauge blocks and the micrometer is the result of a combination of the nominal difference and the associated uncertainties.

7.2.4. Uncertainty of coefficient of thermal expansion

Uncertainty in the coefficient of thermal expansion is a common characteristic of any material. In our study, the values mentioned earlier follow a normal distribution is assumed, which is a common approach for modeling such uncertainties, so

$$\Delta\alpha = \sqrt{U(\alpha_M)^2 + U(\alpha_{GB})^2}$$

where,

$U(\alpha_M)^2$ = the expanded uncertainty ($k = 2$) in the gage block CTE

$U(\alpha_{GB})^2$ = the expanded uncertainty ($k = 2$) in the micrometer CTE

Based on the values above,

$$\Delta\alpha = \sqrt{(1)^2 + (0.5)^2} = 1.12 \times \frac{10^{-6}}{^\circ\text{C}}$$

and,

$$\Delta L = (0.025m) \left(1.12 \times \frac{10^{-6}}{^\circ\text{C}} \right) (2^\circ\text{C}) = 0.056 \mu\text{m}$$

7.2.5. Nominal coefficient of thermal expansion difference

In cases where the nominal coefficient of thermal expansion of the gauge blocks and the micrometer differs, as observed in this study, the following equation is applicable:

$$\Delta\alpha = |\alpha_M - \alpha_{GB}|$$

Where,

α_{GB} = the nominal coefficient of thermal expansion of the gage block.

α_M = the nominal coefficient of thermal expansion of the micrometer.

Based on the values above,

$$\Delta\alpha = |11.5 - 9.3| = 2.2 \times \frac{10^{-6}}{^\circ\text{C}}$$

and,

$$\Delta L = (0.025m) \left(2.2 \times \frac{10^{-6}}{^\circ\text{C}} \right) (2^\circ\text{C}) = 0.11 \mu\text{m}$$

7.2.6. Temperature difference

Considering the influence of handling, it was established that the temperatures of both the micrometer and the gauge blocks could diverge by up to 0.5 °C. In this specific scenario, it is also presumed that available data substantiates the utilization of a normal distribution. The uncertainty arising from this temperature difference can be represented as follows.

$$\Delta L = L\alpha\Delta t$$

where,

L = the nominal length

α = the average coefficient of thermal expansion of the gage blocks and the micrometer

Δt = the difference in temperature between the gage blocks and the micrometer

Based on the values above,

$$\Delta L = (0.025m) \left(10.4 \times \frac{10^{-6}}{^\circ\text{C}} \right) (0.5^\circ\text{C}) = 0.13 \mu\text{m}$$

7.2.7. Repeatability

Uncertainty is a crucial aspect of measurement processes, particularly in precision instruments like micrometers. It pertains to the fluctuation in measurements obtained by measuring the same quantity repeatedly under identical conditions. Quantifying and understanding repeatability uncertainty is essential for assessing measurement reliability and precision, and making critical decisions. The uncertainty due to repeatability, in this case, can be quantified as follows:

Initially, a set of five readings is obtained for a 20.2 mm gauge block. Subsequently, the standard deviation is computed from these readings.

$$s = \sqrt{\frac{\sum (X_i - \bar{X})^2}{N - 1}}$$

where,

X_i = an individual data point

\bar{X} = the mean (average) of the sample.

N = the total number of data points in the sample.

Finally, the standard uncertainty is derived from.

$$\text{Standard uncertainty} = \frac{s}{\sqrt{N}} = \frac{0.00055}{\sqrt{5}} = 0.00025 \mu\text{m}$$

7.2.8. Combined and expanded uncertainty

After establishing the values mentioned earlier, the corresponding standard uncertainties is estimated and proceeded as presented in the provided [Table 1](#). Subsequently, the combined uncertainty, represented as u_c , is computed as follows:

$$u_c = \sqrt{u_1^2 + u_2^2 + \dots + u_n^2}$$

Based on the values above,

$$u_c = \sqrt{0.081^2 + 0.033^2 + 0.028^2 + 0.055^2 + 0.065^2 + 0.00025^2} \\ = 0.1252 \mu\text{m}$$

Expanded uncertainty (U) considers combined uncertainty (u_c) and a coverage factor (k), widening the uncertainty interval to account for unknown factors or measurement variability. The formula for expanded uncertainty (U) is:

$$U = k \times u_c$$

$$U = 2 \times 0.1252 = 0.25 \mu\text{m}$$

Building upon the cornerstone of the $0.001 \mu\text{m}$ μm 's meticulously quantified uncertainty ($0.25 \mu\text{m}$), this study ventures further into the realm of measurement precision. Our objective is to illuminate the uncertainty profiles of two additional tools: simulated tools representing 0.01 and $0.1 \mu\text{m}$ resolution. It's important to note that the gathered measurements have been rounded successively to accuracies of 0.01 mm and then to 0.1 mm . This approach maintains consistency in measurements even with varying levels of precision and provides insights into how the accuracy of measuring tools impacts the measurement of diameters. To achieve this multi-level analysis, the valuable data obtained from the reference standard measurement will be exploited with the caliper. This empirical uncertainty value, obtained through standard from the

ASME B89.1.14–2018 Caliper ([ASMEc](#)), serves as a crucial anchor point for our subsequent estimations. A linear regression analysis was employed to estimate the measurement uncertainty associated with simulated resolution tools (0.01 mm and 0.1 mm). This approach utilizes two data sets: high-precision reference measurements obtained using a 0.001 mm μm for various standard gauge block sizes, and the empirical uncertainty value obtained from the ASME B89.1.14–2018 Caliper standard. The regression analysis establishes a linear relationship between these reference values and a crucial second data point. By analyzing this relationship, the model can estimate the expected uncertainty for measurements obtained using the simulated resolution tools. This incorporation of a standardized uncertainty value enhances the reliability of the estimated uncertainties for the simulated tools. This established statistical approach allows us to infer the relationship between known reference values and corresponding measurements obtained with a higher-accuracy instrument ($0.001 \mu\text{m}$ μm). [Table 2](#) comprehensively presents the uncertainty values ascertained for each of the investigated measurement tools, categorized by their stated accuracy level. Additionally, it illuminates the specific method employed to derive each uncertainty value, providing invaluable context for interpreting the data.

8. Case study

Next, a case study explores the practical application of measurement uncertainty in engineering and manufacturing. It focuses on precise measurements of cylindrical components, highlighting the complexities of accuracy and its impact on decision-making processes through advanced techniques and rigorous statistical analysis.

8.1. Data review

Data from 70 measurements has been gathered, utilizing a micrometer with an accuracy of

Table 2. Unveiling uncertainty profiles: across-methodological exploration.

Accuracy level (mm)	Uncertainty (μm)	Method	Note
0.001	0.25	Calculated	Precise measurement with a reference standard
0.02	1.2	Standard	Manufacturer specification or standard measurement
0.01	0.7	Regression	Estimated using regression analysis.
0.10	5.2	Regression	Estimated using regression analysis.
Equation	$U = 50 \times \text{Accuracy Level} + 0.2$	Regression model	Relates uncertainty to accuracy level (for simulated tools)

0.001 mm. These measurements correspond to the cylinder's diameter.

8.2. Utilized decision rule for quality assessment

The decision rule is a systematic method for allocating measurement uncertainty in determining product acceptance or rejection, considering product specifications and measurement results (ASMEa). This study will use the simple acceptance decision rule for data analysis, followed by an alternative rule to increase product acceptance confidence. The conventional method of simple acceptance and rejection for quality assessment faces challenges when measuring results near specification limits as mentioned in section II.B. Guard banding is an alternative decision rule that is used to deal with this problem and make quality assessment decisions more reliable, especially when measurements are close to the limits of the specification.

8.3. Confirmation to specifications

A control chart was created to visually represent the impact of different accuracy levels on the confirmation process. It calculates the percentage of samples confirmed to specifications for each accuracy level (with accuracies of 0.001, 0.01, and 0.1 mm), providing insights into the confirmation process outcomes, Fig. 4.

The chart shows that some samples initially met specifications with a 0.1 mm accuracy tool but did not align with specifications with a 0.001 mm tool,

highlighting the importance of selecting a measurement tool with appropriate accuracies. The data illustrates a close similarity between the results obtained from a tool with a precision of 0.001 and one with 0.01 accuracy for the part under inspection. Therefore, there is no need to use a high-level accuracy tool of 0.001 for this part accuracy. A tool with the lowest accuracy of 0.01 is sufficient. Recognizing the cost-effectiveness, accessibility, and operational ease of 0.01 accuracy tools compared with their 0.001 counterparts merits their consideration. While sacrificing some precision, the economic advantages, wider availability, and user-friendliness of 0.01 tools present a compelling alternative, particularly when the application's sensitivity to minor discrepancies is outweighed by these practical benefits.

Fig. 5 unveils a crucial association between measurement accuracy and quality control confirmation rates. This relationship, where diminishing accuracy coincides with higher confirmation rates, poses potential risks in manufacturing environments. Essentially, less precise tools elevate the odds of classifying products as compliant, fostering the undetected passage of substandard items.

This phenomenon can be attributed to the inherent limitations of lower-accuracy tools. Their inability to discern subtle deviations from specifications allows potentially defective products to slip through the cracks, compromising the final product quality. This presents a dual threat.

(a) Consumer risk: defective products reaching consumers can erode trust and brand



Fig. 4. Control chart for all accuracy levels.

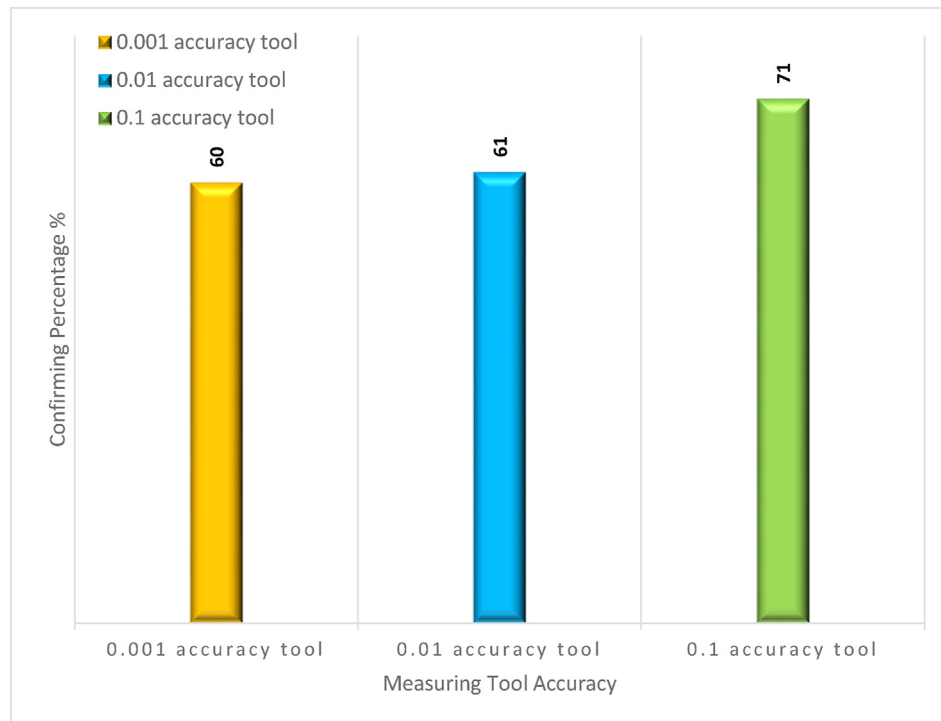


Fig. 5. Trend of confirmation rates as accuracy decreases.

reputation, impacting customer satisfaction and potentially leading to legal repercussions.

- (b) Manufacturer risk: undetected issues can manifest later in the production chain, incurring substantial costs associated with recalls, rework, and reputational damage.

Fig. 5 delves into the nuanced interplay between measurement accuracy, product confirmation rates, consumer risk, and manufacturer reputation. It emphasizes the critical role of precise instruments in quality control, ensuring customer satisfaction and safeguarding the integrity of manufacturing processes, while acknowledging the potential consequences of substandard product delivery. The figure reveals a stark discrepancy: while a less accurate tool confirms 11.41% of products as compliant, these might not truly adhere to specifications. This underscores the crucial need to consider both measurement accuracy and inherent uncertainty when evaluating the quality of seemingly compliant products. The analysis exposes instances where items categorized as conforming with a 0.1 accuracy tool are deemed non-compliant using a 0.001 tool. By presenting two measuring readings for the same product, the chart effectively illustrates how measuring instrument accuracy directly impacts compliance decisions. This reinforces the notion that investing in higher-precision tools can

minimize consumer risk, protect brand reputation, and ultimately contribute to a more robust and reliable manufacturing process.

Fig. 6 visually depicts the importance of selecting appropriate measurement tools for quality control, particularly when dealing with diameter measurements. The graph illustrates a data point that initially falls within the 'confirmation area' when assessed with a 0.1 mm accuracy tool. However, when evaluated with a more precise 0.001 mm tool, the same data point shifts to the 'non-confirmation region.' This stark contrast emphasizes the potential for inaccurate assessments with less precise instruments, potentially leading to.

- (1) Misleading Confirmation: As the graph indicates, using a 0.1 mm tool might lead to misclassifying non-compliant parts as compliant, necessitating Scraping and incurring additional expenses. This is visually represented by the measurement reading initially falling within the 'confirmation area' for the 0.1 mm tool but exceeding the lower tolerance limit when measured with the 0.001 mm tool.
- (2) Financial Losses: Conversely, deviations below specified thresholds, often only identifiable with higher-accuracy tools, can result in scrapped products and significant financial losses. This is evident in the graph by the measurement reading

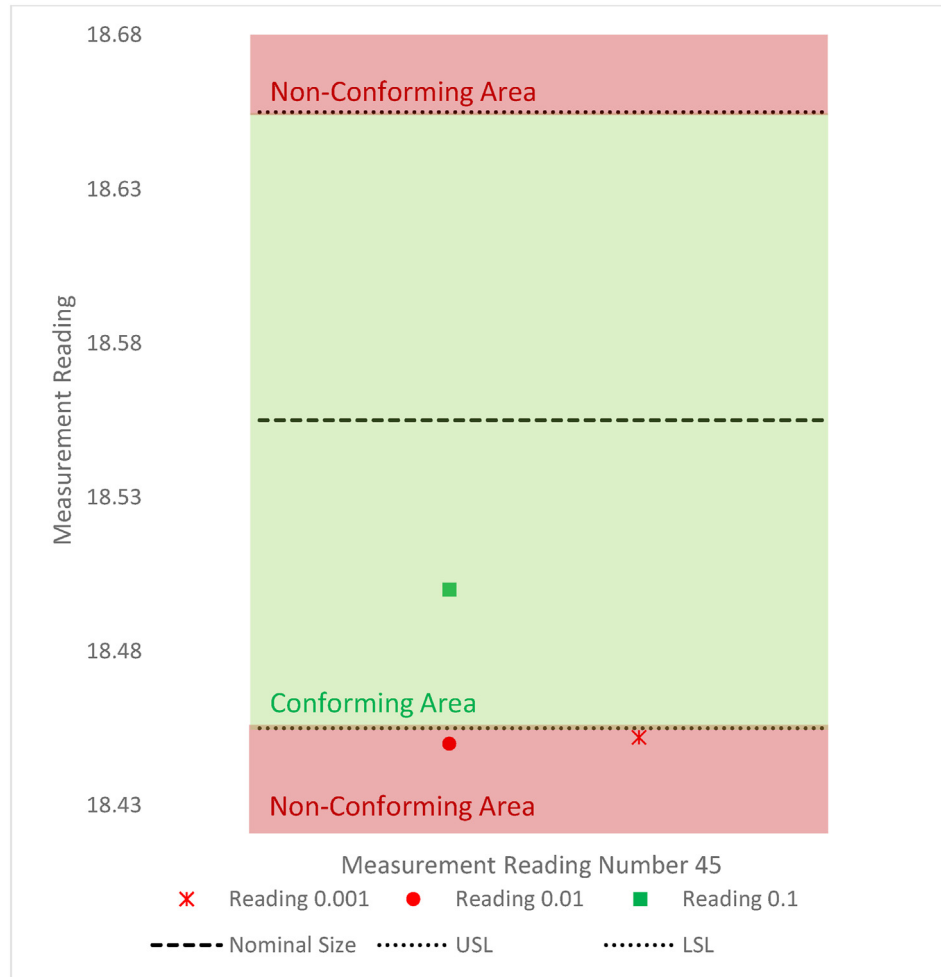


Fig. 6. Effect of accuracy level on part confirmation status.

falling below the lower tolerance limit when measured with the 0.001 mm tool, even though it appeared compliant with the 0.1 mm tool.

Therefore, robust quality assurance measures that incorporate cost-benefit analysis are essential. This analysis involves balancing the initial investment in higher accuracy tools against the long-term benefits they offer, such as.

- (1) **Reduced Risk:** More precise measurements minimize the likelihood of undetected non-compliance, lowering the risk of recalls, rework, and reputational damage.
- (2) **Improved Product Quality:** Enhanced accuracy ensures stricter adherence to specifications, leading to higher-quality products and increased customer satisfaction.

By carefully considering these factors and the potential impact on costs, manufacturers can select

the most cost-effective approach to quality control, optimizing their production processes while safeguarding their financial well-being and brand reputation.

Now, let's delve deeper into the data and visually explore the impact of measurement accuracy on real-world scenarios. A closer look at the specific measurement readings used in the table will be taken to examine how they translate to different outcomes depending on the chosen measurement tool's accuracy (0.001 vs. 0.01 vs. 0.1). By illustrating these contrasting results, a concrete understanding of how inaccurate measurements is provided to manifest tangible costs in various forms, such as rework, scrap, and potential recalls. This visualization will further solidify the economic benefits of prioritizing high-accuracy tools in quality control processes.

Table 3 presents a compelling illustration of the significant impact that measurement accuracy can

Table 3. Impact of measurement accuracy on production costs: rework, scrap, and recall.

Accuracy level	Number of defect parts (rework)	Number of defect parts (scrap)	Number of defect parts (recall)	Cost for rework per 1 product (\$)	Cost for scrap per 1 product (\$)	Cost for recall per 1 product (\$)	Rework cost (\$)	Scrap cost (\$)	Recall cost (\$)	Total cost (\$)
0.001	10	18	0	4	10	25	40	180	0	220
0.01	10	17	1	4	10	25	40	170	25	235
0.1	10	10	8	4	10	25	40	100	200	340

have on production costs across three key areas: rework, scrap, and recall. By comparing the cost implications of using three different measurement accuracies (0.001, 0.01, and 0.1), the table reveals stark differences in cost efficiency. The analysis sheds light on the potential cost savings achievable through implementing higher-accuracy measurement tools, highlighting their economic benefits beyond ensuring product quality and regulatory compliance.

This table comprehensively portrays the significant impact varying measurement accuracy levels (0.001, 0.01, and 0.1) can have on production costs across three categories: rework, scrap, and recall. Each category details the number of defective parts identified, the associated per-unit cost, and the total cost incurred for the production volume. Valuable insights into the economic advantages of prioritizing high-accuracy measurements can be gleaned by meticulously dissecting this data. While the difference between 0.001 and 0.01 accuracy levels may seem comparatively close, it is important to recognize that even seemingly minor discrepancies in measurement can have significant downstream effects. This analysis will primarily focus on comparing the 0.001 and 0.1 accuracy levels due to the potentially substantial cost and quality implications associated with the larger disparity. This approach allows for a more targeted examination of the impact of measurement accuracy on key areas like production efficiency, product quality, and potential financial losses. Valuable insights into optimizing quality control processes and maximizing returns can be gained by delving deeper into the cost-benefit analysis of these accuracy levels.

The elevated costs associated with the 0.1 accuracy tool can be attributed to its inherent limitations in detecting subtle deviations from specified tolerances. These undetected issues can manifest in several ways.

(a) Rework: noncompliant parts that do not meet the specified tolerance limits during inspection due to inaccurate measurements necessitate rework later in the production process, incurring additional labor and material costs. While the

initial detection of 10 defective parts across all accuracy levels might suggest similar performance, it is crucial to avoid the misinterpretation of this finding as evidence for the 'perfection' of all measurement tools. This conclusion fails to consider the broader picture of downstream costs associated with undetected noncompliance. Analyzing scrap and recall costs reveals a more nuanced story, highlighting the significant economic advantages of employing high-accuracy tools.

(b) Scrap: deviations exceeding specified tolerances, missed by the less precise tool, lead to scrapped parts, resulting in wasted materials and lost production time. While analyzing the table data, one might be tempted to conclude that the 0.1 accuracy tool offers an advantage in scrap cost due to its higher number of 'passed' parts. However, this seemingly positive outcome masks a critical caveat: undetected deviations from specifications. The seemingly lower scrap cost associated with the 0.1 tool stems from its inability to identify parts with minor deviations that fall within its wider tolerance range. These undetected non-compliant parts, while initially escaping scrap, are more likely to surface later in the production process or even reach consumers, potentially triggering costly recalls. The cost of downstream rework and potential recalls significantly outweigh the immediate benefit of lower scrap with the 0.1 tool.

(c) Recall: products reaching consumers with undetected non-compliance issues can trigger costly recalls, damaging brand reputation and potentially leading to legal repercussions. The table reflects an identical per-unit cost for recalls across all accuracy levels. However, the crucial caveat lies in the number of defective parts identified for recall. The 0.001 tool detects only zero units, minimizing recall risk, while the 0.1 tool identifies 8 defective parts, exponentially increasing the potential for costly recalls.

This comprehensive analysis underscores the undeniable economic benefits associated with employing high-accuracy measurement tools (0.001)

in quality control processes. By minimizing rework, scrap, and potential recall costs, the 0.001 tool offers not only significant cost savings but also enhances product quality and safeguards brand reputation. While the seemingly minor difference between 0.001 and 0.01 accuracy might appear negligible, the data demonstrates that, in this context, even minute discrepancies in measurement precision can translate into substantial economic and qualitative advantages. Therefore, while the 0.1 tool might show lower scrap costs initially, its limited detection capability poses a higher risk of costly recalls and reputational damage, ultimately negating any perceived economic advantage. In contrast, high-accuracy tools (0.001 and 0.01), despite generating slightly higher scrap costs initially, offer a significant net benefit by minimizing undetected deviations and subsequent downstream costs, ensuring product quality and compliance, safeguarding brand reputation and reducing the risk of recalls and associated legal/regulatory consequences. In conclusion, prioritizing high-accuracy tools represents a strategically sound and cost-effective approach, even if it appears to generate slightly higher initial scrap costs. Their superior detection capabilities minimize the risk of costly downstream incidents and uphold product quality and brand integrity, ultimately leading to greater economic and reputational value in the long run.

While Figs. 7 and 8 present valuable insights into defect detection across different accuracy levels, drawing conclusions solely based on individual figures can be misleading. To accurately assess the ‘perfection’ of the 0.001 accuracy tool, a

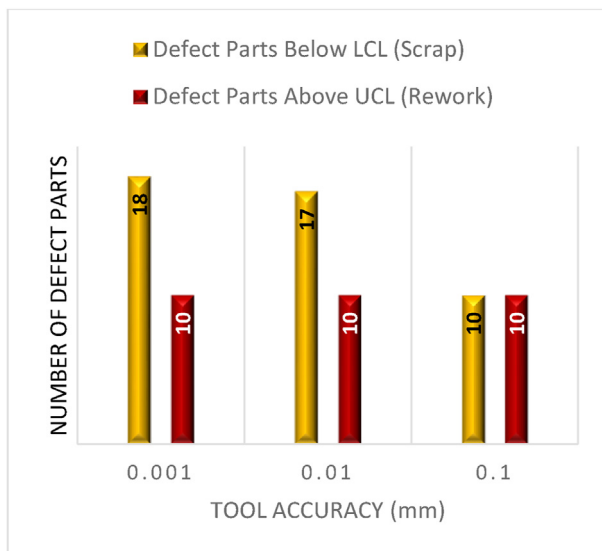


Fig. 7. Scrap and rework counts at different accuracy levels.

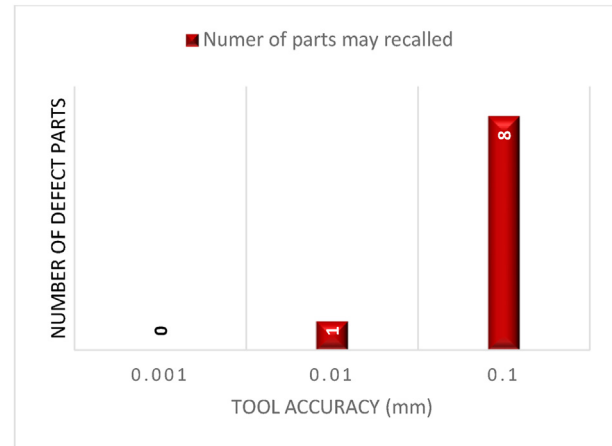


Fig. 8. Recall risk across accuracy levels.

comprehensive examination considering both charts is crucial. Fig. 10, displaying scrap and rework data, might initially suggest the 0.1 accuracy tool as the ‘best’ due to its lower scrap values. However, this apparent advantage masks a critical issue: undetected deviations. The 0.1 tool’s wider tolerance range allows non-compliant parts to pass through, leading to downstream costs in rework and potential recalls (reflected in Fig. 8). These hidden costs ultimately overshadow any initial benefit of lower scrap. Fig. 8 unveils the true impact of undetected deviations. The significantly lower recall risk associated with the 0.001 tool translates to substantial cost savings, negating the seemingly lower scrap cost of the 0.1 tool. This highlights the 0.001 tool’s effectiveness in preventing costly downstream issues and safeguarding product quality. Examining both figures in tandem paints a more complete picture. While the 0.1 tool appears ‘perfect’ in Fig. 7, its inability to detect minor deviations exposes its limitations. Conversely, the 0.001 tool, despite potentially generating slightly higher scrap initially, demonstrates its ‘perfection’ through preventative measures that minimize downstream costs and ensure product quality, ultimately leading to greater overall efficiency and economic benefit.

Fig. 9 presents a compelling visual portrayal of the total cost implications associated with different measurement accuracy levels (0.001, 0.01, and 0.1) across three categories: rework, scrap, and recall. This combined representation effectively addresses the potential misinterpretations arising from analyzing individual figures and delivers a clear message regarding the true ‘perfection’ of the 0.001 accuracy tool. The most striking feature is the distinctly lower total cost associated with the 0.001 accuracy tool compared with both the 0.01 and 0.1

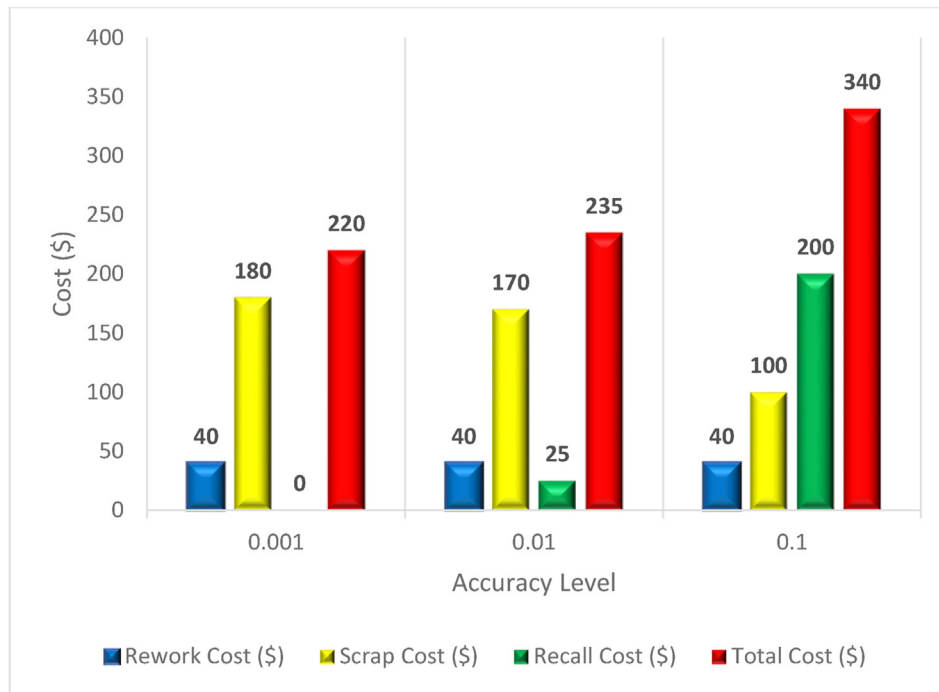


Fig. 9. Total cost of different accuracy levels.

tools. This visual representation solidifies the notion that seemingly minor differences in accuracy can translate into significant economic benefits. Unlike Fig. 10, which might have suggested an advantage for the 0.1 tool in scrap cost, Fig. 8 incorporates the downstream impact of undetected deviations through recall costs. This holistic view reveals the hidden costs associated with the 0.1 tool, ultimately negating any initial scrap cost advantage. The chart visually emphasizes the preventative nature of the 0.001 tool's superior accuracy. By minimizing scrap and recall risks, it avoids the need for costly rework and corrective actions, leading to a more efficient and cost-effective production process.

8.4. Risk analysis

It is crucial to delve deeper into how this uncertainty translates into concrete risk assessment. Therefore, the focus has now shifted to the relationship between measurement readings, uncertainty, and specification limits. Assuming a normal distribution for uncertainty, this statistical framework can be leveraged to calculate the risk of two critical scenarios: falsely accepting a defective part and rejecting a good part.

Here's an explanation of how to calculate consumer and producer risks using measured value, uncertainty, and the specification limit near it in Excel. Some assumptions are necessary for this

calculation. First having a measured value for a part characteristic, the uncertainty associated with the tool used for measurement, and having the relevant specification limit (upper specification limit (USL) or Lower Specification Limit (LSL)) for the part characteristic.

Steps.

- (i) Determine the relevant specification limit:
 - (a) If the measured value is closer to the USL, use the USL in the calculation. This scenario assesses the consumer risk, the risk of accepting a non-conforming part that is actually outside the tolerance limits.
 - (b) If the measured value is closer to the LSL, use the LSL in the calculation. This scenario assesses the producer risk, the risk of rejecting a conforming part that is actually within the tolerance limits.
- (ii) Calculate the risk using the Normal Distribution Function (NORM.DIST):
 - (a) Excel provides the NORMDIST function to calculate the cumulative probability distribution for the standard normal distribution.
 - (b) Depending on the type of risk calculated, use the appropriate formula:

NORM.DIST(x (specification limit), mean (measured value), standard_dev (uncertainty), cumulative).

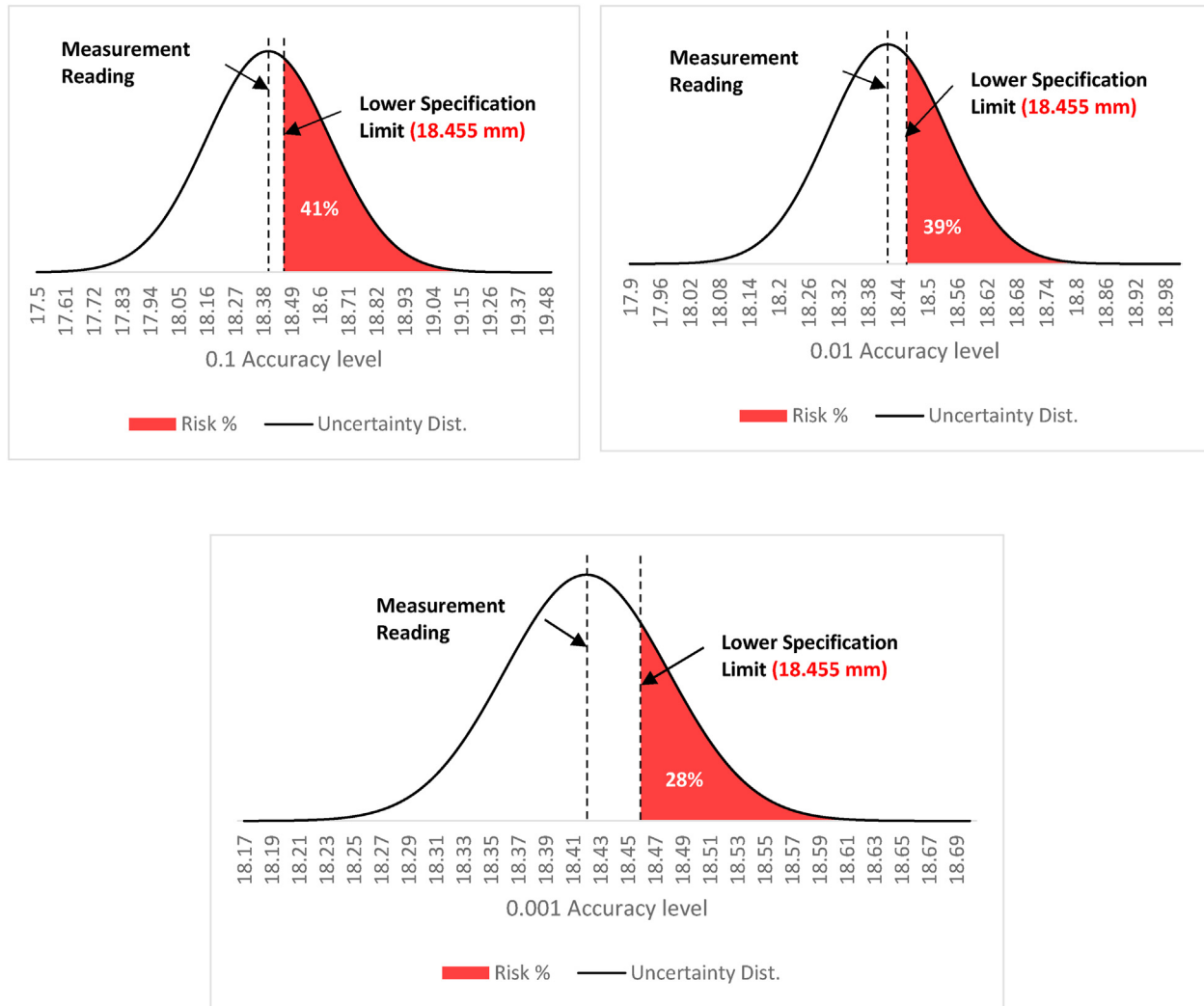


Fig. 10. Consumer risk at measurement number three.

8.4.1. False acceptance risk

Imagine a measured value near the USL. Here, a high uncertainty could potentially obscure actual deviations exceeding the limit, leading to falsely accepting a defective part. To quantify this risk, the cumulative distribution function (CDF) of the normal distribution can be utilized. The CDF, with the measured value, uncertainty and the USL as parameters, represents the probability of obtaining a value below that specification limit. This probability essentially translates to the risk of falsely accepting a defective part.

8.4.2. False rejection risk

Similarly, consider a measured value near the lower specification limit. High uncertainty might lead to rejecting a good part that falls within the acceptable range. The commentary CDF representing the probability of obtaining a value below the

lower specifications limit, quantifies the risk' likely refers to the consumer risk, not the sum of both risks. The sum of false acceptance risk and false rejection risk (producer risk + consumer risk) does not necessarily equal 1. If the measured value with uncertainty falls entirely within or outside the acceptance zone, both risks become zero because there's no chance of an incorrect decision. While achieving this error-free scenario is ideal, it is not always feasible in practice due to inherent measurement limitations. Measurement uncertainty often creates a 'gray area' where the uncertainty range overlaps the acceptance zone boundaries. By calculating these probabilities for various scenarios (different measured values, uncertainties, and specification limits), a comprehensive risk map can be constructed. This map visually depicts the impact of uncertainty on risk, empowering informed decision-making in selecting appropriate tools and

tolerance levels. The CDF employed in this analysis exhibits a context-dependent approach when considering specification limits. The CDF focuses on the USL if the measured value is closer to it. This essentially assesses the risk of exceeding the acceptable upper bound by calculating the probability of obtaining a value even higher than the measured value (accounting for its inherent uncertainty). However, there are scenarios where the measured value is closer to the LSL, as exemplified by measurement 3 in Fig. 10. In these cases, the CDF calculation shifts its focus to the LSL. Here, the objective is to evaluate the risk of falling below the acceptable lower bound by determining the probability of obtaining a value lower than the measured value (considering its uncertainty).

A meticulous analysis of the calculated risks associated with different measurement tool accuracy levels reveals a compelling trend: investing in tools with 0.001 mm accuracy significantly reduces the risk for both producers and consumers. This finding underscores the substantial benefits of prioritizing higher accuracy in quality control decisions. By minimizing both producer risk (accepting defective parts) and consumer risk (receiving subpar products), high-accuracy tools lead to more accurate and reliable acceptance decisions. This translates to enhanced product quality, increased consumer trust, and reduced potential for costly recalls or rework.

The significantly lower consumer risk associated with the 0.001 μm tool compared with less precise options speaks volumes about the impact of accuracy. This reinforces the notion that while the initial investment in higher-accuracy tools might appear higher, the downstream benefits in terms of risk mitigation and overall production efficiency make it a financially sound and value-driven choice. By minimizing uncertainty and ensuring adherence to tight tolerances, high-accuracy tools contribute to robust production processes, ultimately leading to.

- (a) Reduced rework and scrap costs: Fewer defective parts accepted and rejected parts that adhere to specifications.
- (b) Enhanced brand reputation: Consistent product quality fosters consumer trust and loyalty.
- (c) Lowered legal and regulatory risks: compliance with safety and quality standards is ensured.

This study delves into the crucial relationship between measurement uncertainty and risk analysis, specifically focusing on measurement number 3. The impact of reduced precision on the likelihood of falsely accepting defective parts was meticulously

analyzed by employing tools with varying accuracy levels (0.001, 0.01, and 0.1). This investigation utilizes diverse analytical tools to comprehensively present the risk landscape. Fig. 10 visually depicts the calculated consumer risk percentages for each accuracy level, effectively demonstrating the significant rise in risk with decreasing precision. The figure also shows the impact of measurement uncertainty on the risk of falsely accepting a defective part (consumer risk) for measurement number three.

Consumer risk increases significantly with decreasing accuracy levels. At 0.001 accuracy, the risk is only 28%, while at 0.1 accuracy, it jumps to 41%. The shaded areas within the normal distributions illustrate the probability of exceeding the lower specification limit, confirming the increased risk with lower accuracy. Fig. 11 showcases the measured values at different accuracy levels alongside their associated uncertainties represented by error bars. This visualization directly demonstrates the relationship between accuracy level and measurement uncertainty. Error bars grow noticeably larger with decreasing accuracy levels, signifying the increasing spread of potential measurement values. The 0.001 accuracy level stands out with the smallest error bars, indicating its ability to deliver highly precise measurements. This visual representation reinforces the trade-off between accuracy and uncertainty, highlighting the potential consequences of using less precise tools.

The combined uncertainty values directly correspond to the error bar sizes in Fig. 11, quantitatively confirming the observed trend. The increasing consumer risk percentages across accuracy levels align with the visual representation in Fig. 10. Notably, despite being marginally closer to the lower specification limit, the 0.001 accuracy tool offers a significant advantage over the 0.1 accuracy tool in terms of risk mitigation. This critical advantage is quantified by the consumer risk percentages presented in this analysis. At 28%, the 0.001 accuracy tool boasts a remarkably lower risk compared with the 41% risk associated with the 0.1 accuracy tool. This 13% difference translates to a substantial reduction in the probability of accepting non-compliant products, safeguarding consumer safety and product integrity. The underlying reason for this disparity lies in the inherent trade-off between accuracy and uncertainty. Lower accuracy levels, like 0.1, lead to wider distributions of potential measurement values, increasing the overlap with the non-compliant region below the lower specification limit. This overlap represents the shaded area in Fig. 10, visually highlighting the elevated risk of

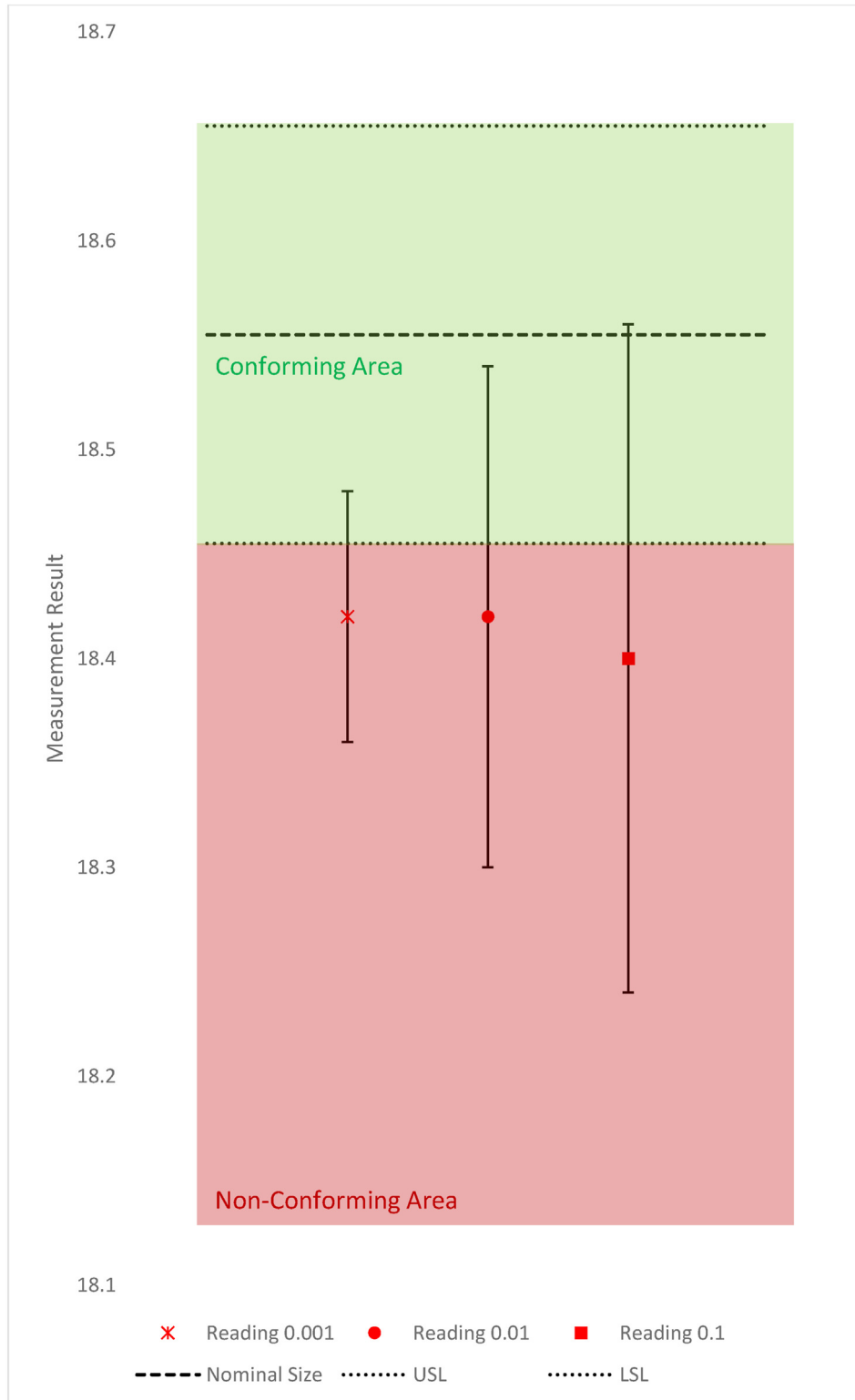


Fig. 11. Measurement readings with uncertainty.

wrongly accepting defective parts. Conversely, the high precision achieved by the 0.001 tool minimizes this overlap, shrinking the shaded area and consequently reducing the consumer risk to a

considerably lower level. The combined analysis of Figs. 10 and 11 underscores the crucial role of measurement accuracy in mitigating consumer risk. By employing tools with higher accuracy (e.g.,

0.001), the risk of accepting defective parts significantly decreases, ensuring better product quality and consumer safety. This finding underlines the importance of carefully selecting appropriate measurement tools based on specific risk tolerance and quality requirements.

Therefore, while the 0.001 accuracy tool might come at a higher initial cost, its substantial reduction in consumer risk translates to tangible benefits in several key areas.

- (a) Enhanced product quality and safety: minimizing the acceptance of defective parts leads to better-performing and safer products, safeguarding consumer well-being.
- (b) Reduced rework and production costs: detecting noncompliant items early in the production process minimizes costly rework and scrappage.
- (c) Improved brand reputation: consistent adherence to quality standards fosters consumer trust and strengthens brand image.

This analysis underscores the importance of moving beyond a mere focus on stated accuracy levels and delving deeper to understand the impact of uncertainty and associated risks. By considering these factors, organizations can make informed decisions regarding measurement tools, ensuring optimal balance between cost, accuracy, and risk mitigation in their quality control processes. In conclusion, this investigation into risk analysis within the specific measurement scenario underscores the critical role of employing high-accuracy tools, particularly those with a 0.001 level. By minimizing both producer and consumer risks, this approach promotes efficient production, ensures product safety, and enhances trust among producers and customers.

9. Conclusion

The study explores the relationship between quality control strategies, accuracy levels, tolerance limits, and risks in manufacturing, emphasizing the need for data-driven, product-specific approaches to balance cost, quality, and risk. It highlights the importance of critical data points near control limits for process stability, reliability, and quality control, emphasizing the significant impact of measurement accuracy. The observed 11.43% discrepancy in part acceptance between 0.001 mm and 0.1 mm accuracy tools highlights the importance of precision in safeguarding product quality. It cautions against using lower accuracy tools to reduce rejection rates, citing increased consumer risk and reputational damage,

emphasizing the complex relationship between accuracy and cost in quality control. The results revealed that while precision is important, context and cost-effectiveness should be considered. The 0.01 mm tool offers advantages over the 0.1 mm tool, minimizing false positives and adapting to future needs. Manufacturers should conduct a thorough cost-benefit analysis and evaluate specific requirements to optimize accuracy, ensuring product quality and financial sustainability. Balancing accuracy, tolerance, risk assessment, and cost optimization are crucial for long-term operational success.

- (a) This study explores how quality control strategies, measurement accuracy, tolerance limits, and risks are all interconnected in manufacturing.
- (b) It emphasizes the importance of using data specific to each product to find the right balance between cost, quality, and risk.
- (c) Critical data points near control limits are essential for maintaining process stability, reliability, and good quality control. This highlights how important measurement accuracy is.
- (d) The study found a big difference (11.43%) in part acceptance rates between using high-precision (0.001 mm) and low-precision (0.1 mm) tools. This shows how precision is crucial for safeguarding product quality.
- (e) The study warns against using lower accuracy tools just to reduce rejection rates. This can increase the risk of accepting bad parts (consumer risk) and damage the company's reputation. It highlights the complex relationship between accuracy and cost in quality control.
- (f) While precision is important, the study found that it's also necessary to consider the specific situation and cost-effectiveness. The 0.01 mm tool was better than the 0.1 mm tool because it reduced false positives and could be used for future needs as well.
- (g) Manufacturers should carefully analyze the costs and benefits of different accuracy levels and consider their specific needs. This will help them find the optimal accuracy level to ensure product quality and financial health.
- (h) Overall, balancing accuracy, tolerance limits, risk assessment, and cost optimization is essential for a manufacturing operation to be successful in the long run.

Author contribution/author credit statement

Mostafa A. Sedeek: Conceived and designed the study, contributed to data analysis and interpretation, performed investigations, contributed to

methodology development, conducted statistical analysis, and drafted the article.

Fatma A. Elerian: Contributed to data analysis and interpretation, performed investigations, and revised the article.

Ossama B. Abouelatta: Conceived and designed the study, contributed to data analysis and interpretation, contributed to methodology development, conducted statistical analysis, supervised the study, critically revised the article, and provided final approval of the version to be published.

Mona A. AbouEleaz: Conceived and designed the study, contributed to data analysis and interpretation, performed investigations, contributed to methodology development, conducted statistical analysis, supervised the study, and critically revised the article.

Conflict of interest

There are no conflicts of interest.

References

- 17000 II, 2004. Conformity Assessment—Vocabulary and General Principles. International Organization for Standardization/International.
- Adams, T.M., 2008. G103-A2LA Guide for Estimation of Uncertainty of Dimensional Calibration and Testing Results. The American Association for Laboratory Accreditation, pp. 1–30.
- Alkhatib, H., Neumann, I., Kutterer, H., 2009. Uncertainty Modeling of Random and Systematic Errors by Means of Monte Carlo and Fuzzy Techniques.
- ASME. ASME B89.7.3.1-2001: Guidelines for Decision Rules: Considering Measurement Uncertainty in Determining Conformance to Specifications. ASME New York.
- ASME. ASME-B89.1.13-2013(R2022). The American Society of Mechanical Engineers.
- ASME. ASME B89.1.14-2018 Caliper. The American Society of Mechanical Engineers.
- Bell, S.A., 2001. A Beginner's Guide to Uncertainty of Measurement.
- Božanić, D., Pamučar, D., Milić, A., et al., 2022. Modification of the logarithm methodology of additive weights (LMAW) by a triangular fuzzy number and its application in multi-criteria decision making. *Axioms* 11, 89.
- Current issues in uncertainty of dimensional tolerance metrology and the future development in the domain of tolerancing. In: Meirbek, M., Meifa, H., Zhemin, T. (Eds.), 2020. IOP Conference Series: Materials Science and Engineering. 715(1), 3rd International Conference on Material Engineering and Advanced Manufacturing Technology 26–28 April 2019, Shanghai, China. 012084. IOP Publishing.
- Committee, E.L., 2013. Evaluation of the Uncertainty of Measurement in Calibration EA-4/02. European Accreditation. <http://www.european-accreditation.org>.
- Desimoni, E., Brunetti, B., 2011. Uncertainty of measurement and conformity assessment: a review. *Anal. Bioanal. Chem.* 400, 1729–1741.
- Ellison, S., Williams, A., 2007. Use of uncertainty information in compliance assessment (Eurachem/CITAC Guide). Hely Nelk. Eurachem. 1–15.
- He, X., Yang, H., Hu, Z., et al., 2022. Robust lane change decision making for autonomous vehicles: an observation adversarial reinforcement learning approach. *IEEE Transact Intell Vehicle* 8, 184–193.
- ILAC-G8:09/2019, 2019. Guidelines on Decision Rules and Statements of Conformity, pp. 1–20.
- Jalid, A., Hariri, S., Laghzale, N., 2015. Influence of sample size on flatness estimation and uncertainty in three-dimensional measurement. *Int J Metrol Quality Eng* 6, 102.
- Jcgm, J., 2008. Evaluation of measurement data—guide to the expression of uncertainty in measurement. *Int Organ Stand Geneva* 50, 134.
- JIS. JIS B-7502-2016 Micrometers. Japanese Industrial Standard.
- Kandavalli, S.R., Khan, A.M., Iqbal, A., et al., 2023. Application of sophisticated sensors to advance the monitoring of machining processes: analysis and holistic review. *Int. J. Adv. Manuf. Technol.* 125, 989–1014.
- Kumar, S., Gopi, T., Harikeerthana, N., et al., 2023. Machine learning techniques in additive manufacturing: a state of the art review on design, processes and production control. *J. Intell. Manuf.* 34, 21–55.
- Lifton, J.J., 2023. Evaluating the standard uncertainty due to the voxel size in dimensional computed tomography. *Precis. Eng.* 79, 245–250.
- Majda, P., Jastrzębska, J., 2021. Measurement uncertainty of generalized stiffness of machine tools. *Measurement* 170, 108692.
- Niu, B., Xu, H., Chen, L., 2022. Creating all-win by blockchain in a remanufacturing supply chain with consumer risk-aversion and quality untrust. *Transport. Res. E Logist. Transport. Rev.* 163, 102778.
- Pendrill, L.R., 2006. Optimised measurement uncertainty and decision-making when sampling by variables or by attribute. *Measurement* 39, 829–840.
- Pendrill, L.R., 2014. Using measurement uncertainty in decision-making and conformity assessment. *Metrologia* 51, S206.
- Petousis, M., Vidakis, N., Mountakis, N., et al., 2023. Compressive response versus power consumption of acrylonitrile butadiene styrene in material extrusion additive manufacturing: the impact of seven critical control parameters. *Int. J. Adv. Manuf. Technol.* 126, 1233–1245.
- Psarommatis, F., Kiritsis, D., 2022. A hybrid Decision Support System for automating decision making in the event of defects in the era of Zero Defect Manufacturing. *J. Indust. Info. Integration.* 26, 100263.
- Rachakonda, P., Ramnath, V., Pandey, V., 2019. Uncertainty evaluation by Monte Carlo method. *Mapan* 34, 295–298.
- Shi, S., Haitjema, H., Wang, Y., et al., 2021. Uncertainty evaluation and reduction in three-probe roundness profile measurement based on the system transfer function. *Precis. Eng.* 68, 139–157.
- Vives, M.-L., Heffner, J., FeldmanHall, O., 2023. Conceptual representations of uncertainty predict risky decision-making. *Cognit. Affect Behav. Neurosci.* 23 (3), 491–502.
- Uncertainty of measurement and reliability of the decision making on compliance. In: Volodarsky, E., Warsza, Z.L., Kosheva, L.A., et al. (Eds.), 2020. *Automation 2019: Progress in Automation, Robotics and Measurement Techniques*. Springer International Publishing, pp. 672–683.
- Wu, C.-W., 2013. Process performance evaluation based on Taguchi capability index with the consideration of measurement errors. *Int. J. Syst. Sci.* 44, 1386–1399.