Causes of Non-normality of Monitored Quality Characteristics in Process Capability Analysis

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ABSTRACT

Purpose: In process capability analysis, violation of the normality assumption is considered a non-standard situation. This paper defines and categorises causes of non-normality in manufacturing processes, which are essential for quality planning, control, and selecting appropriate analytical procedures. Based on a literature review and systematic investigation, four main categories have been identified. Each category is analysed in detail with practical implications for capability analysis. The paper provides a comprehensive framework for identifying non-normality causes and guiding further analysis steps.

Methodology/Approach: Systematic literature review and expert synthesis of causes, supported by practical examples and categorisation into four key areas

Findings: four categories of non-normality causes identified; each requires a specific analytical approach before capability analysis can proceed

Research Limitation/Implication: Focuses on categorisation; future work should develop automated detection methods and validate solutions across diverse industries

Originality/Value of paper: Provides first comprehensive framework for identifying non-normality causes in manufacturing, bridging theory and industrial practice

Category: Technical paper

Keywords: non-normality of data; causes of non-normality, process capability analysis

Research Areas: Quality Engineering

1 INTRODUCTION

Evaluation of the capability of manufacturing processes is an integral part of product quality planning and management. Process capability analysis provides key information on whether the process can produce products of the required quality. The basic prerequisites for assessing process capability are the process in control and the normality of the observed quality characteristic. Standard capability indices assume normality and are used to assess process capability.

In the practical application, particularly in relation to the fulfilment of the required prerequisites, a number of errors can be encountered in the process capability analysis – data normality is not verified, process capability is evaluated even if normality is not met, an inappropriate statistical test is chosen to assess normality, the interpretation of the results is limited to the achievement or non-achievement of the desired valued of the selected capability index, etc. In case of non-normality, users usually do not know how to interpret and work with other probability distributions.

The behaviour of real production processes commonly shows violations of basic assumptions for process capability analysis. The situation where the process is in control and data come from a normal distribution is rather rare. In some cases, the normality of the observed characteristic can be artificially created (Nepraš and Plura, 2015) as well as the use of different customer strategies to evaluate process capability show different results (Nepraš and Plura, 2016). The International Organisation for Standardisation has submitted the set of ISO 22514 standards. The ISO 22514-2 (2017) standard provides a framework for estimating process performance and process capability for different cases of changes in the distribution of the quality characteristic of interest over time. These changes are categorised based on the stability of the process average and the stability of the process standard deviation in the case of constant, systematic, or random changes. The ISO 22514 series of standards, as well as the AIAG handbook – Statistical Process Control (AIAG, 2005) do not provide sufficient guidance to further specify how to proceed when data normality is not met.

Based on the literature review, no studies focused on listing the causes of non-normality in relation to process capability analysis were found in the research area. The studies usually already work with a specific probability distribution as (Hosseinifard et al., 2009; Senvar and Sennaroglu, 2016; Thavorn and Sudasna-Na-Ayudthya, 2022; Yang and Zhu, 2018a) for which they present the most appropriate analysis procedure or present new or modified capability indices (Alevizakos et al., 2018; Rao et al., 2019; Alevizakos and Koukouvinos, 2020; Wang et al., 2021) instead of identifying the cause of non-normality and determining the appropriate capability analysis procedure.

Hundreds of research articles were reviewed by the author as part of the research. As a complement, the AI tool Consensus (CONSENSUS, 2025) was also used to examine over 200 million peer-reviewed research articles and extract key findings from them. It is designed to speed up the search and increase accuracy in finding relevant information. The main conclusion of the search is that data non-normality is often due to process-specific factors such as equipment failures, deviations due to special causes, measurement errors and the presence of outliers.

2 METHODOLOGY

This study employs a qualitative research methodology based on a systematic literature review and expert synthesis. Over 200 peer-reviewed articles were examined using both manual review and the AI tool Consensus, which enabled efficient extraction of relevant findings from a large corpus of scientific publications. The goal was to identify, categorise, and analyse the causes of non-normality in manufacturing process data, particularly in the context of process capability analysis. The reviewed sources span statistical methods, quality engineering standards, and practical case studies from industrial environments. The categorisation of causes was supported by the author's own experience in manufacturing organisations and illustrated using a structured tool such as the Ishikawa diagram.

The significant contribution of this research lies in the creation of a comprehensive framework that systematically maps the causes of non-normality into four distinct categories: data characteristics, data structure, data collection methodology, and measurement systems. Unlike previous studies that focus on specific distributions or propose alternative capability indices, this paper emphasises the importance of understanding the origin of non-normality before selecting an appropriate analytical approach. The framework provides practical guidance for quality professionals and researchers, enabling more accurate and reliable process capability assessments in real-world manufacturing settings.

3 CAUSES OF FAILURE TO MEET NORMALITY

Data non-normality can be caused by several reasons that fundamentally affect process capability analysis procedures. Some causes do not prevent the capability analysis from proceeding, while other causes must be eliminated prior to the capability analysis because they would lead to unreliable results. It is desirable to consider the analysis of the causes of non-normality as one of the key phases of the process capability analysis. A non-normal distribution may not be the result of special causes, and yet the distribution may have an asymmetric shape. Similarly, normality does not guarantee the absence of special causes that affect the process. This means that some identifiable causes can alter the process without breaking the symmetry or unimodality of the distribution (AIAG, 2005). Similarly, a statement of non-normality may not be correct, e.g. when using an inappropriate test.

Understanding the causes of normality violations in manufacturing processes is essential for accurate quality control and process improvement. Based on an analysis of published articles and a systematic examination of the causes of normality assumption violations in manufacturing process data, four main categories were identified that reflect different aspects of non-normality. The different categories and associated causes are illustrated using the Ishikawa diagram in Figure 1. Each category represents a specific area in which the normality assumption may be violated.

The categories are defined as follows:

- data characteristics,
- data structure,
- data collection methodology,
- measurement systems.

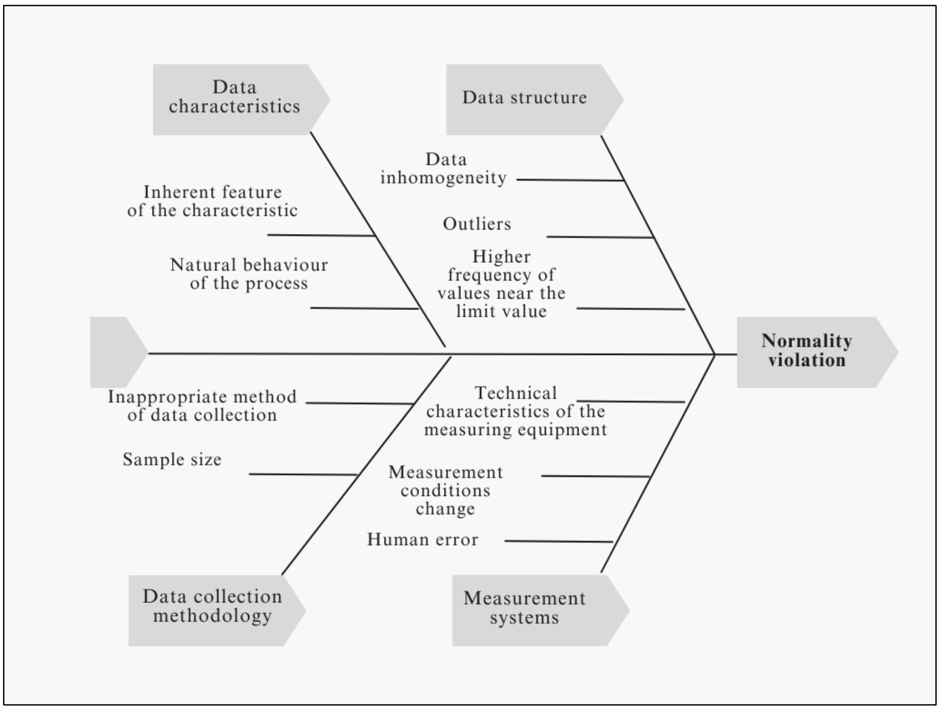

Figure 1 – Causes leading to violations of normality. Source: Author's own work.

This categorisation provides a comprehensive view of the possible causes of non-normality and serves as a basis for further analysis. In the next chapter, the individual causes will be discussed.

3.1 Data characteristics

This category includes causes of non-normality that are based on the natural feature of the quality characteristic or process under study. These are situations where the very nature of the data – its physical, chemical or technological properties – predetermines its distributions. This category is important to understand that not all data necessarily follow a normal distribution, and that statistical analysis must respect the inherent nature of the characteristic being observed.

3.1.1 Inherent feature of the observed quality characteristics

Non-normality as an inherent property of the characteristic under study means that the feature does not naturally exhibit a normal distribution. It is often a physical property of the characteristic; the probability distribution is skewed, and mostly only one tolerance limit is given. Examples are geometric deviations in shape and position, which are often used in practice, and which are usually not characterised by a normal distribution. Real samples may also show higher kurtosis (compared to the normal distribution).

In the case of non-normality in the data that is due to an inherent feature of the observed quality characteristic, standard capability analysis procedures for data that do not follow a normal distribution, namely quantile methods or transformation techniques, may be applied. The quantile-based approach is particularly useful for skewed data and is supported by many studies, e.g. (Taib and Alani, 2021; Karakaya, 2024). The quantile method consists of finding a suitable probability distribution model and using it to determine the appropriate quantiles to express the true variability of the characteristic of concern. Transformation techniques are based on the conversion of the data to new data that fit a normal distribution. An appropriately chosen transformation function leads to stabilisation of the variance, better symmetry of the data, and often to a normal distribution. The effectiveness of these transformations in analysing process capability for non-normal data is demonstrated, for example, by (Yang et al., 2018; Yang and Zhu, 2018b; Borucka et al., 2023; Lavrač and Turk, 2024).

Comprehensive reviews and comparative studies provide practical guidance on selecting appropriate methods based on the degree and type of non-normality (e.g., skewness, kurtosis). These studies (Tang and Than, 1999; Hosseinifard and Abbasi, 2012; Taib and Alani, 2021) emphasise that the choice between quantile methods and transformation techniques should be based on the specific characteristics of the data and the process under study.

In manufacturing processes, the most common non-normal probability distributions include log-normal, Weibull, exponential, gamma, and Cauchy distributions, which better capture the asymmetry of distributions, skewness, or heavy tails of data typical of real manufacturing processes. Among the frequently occurring distributions, the Burr distribution can also be included, which is very flexible and can model a wide range of non-normal distributions of the observed quality characteristics (Chou and Chen, 2017; Chen, 2018). Selected distributions and their brief characteristics are listed in Table 1.

Table 1 – Selected probability distributions and their characteristics. Source: Author's own work.

Distribution	When to Use it	Properties
Log-normal	Values increase or decrease multiplicatively (e.g., wear)	Asymmetry; long-right tail
Weibull	Modelling of degradation, lifetime, and material wear	Asymmetry; shape depends on the shape parameter
Exponential	Modelling of time to first random event	Right-skewed distribution
Gamma	Cumulative effects (e.g., error accumulation, time until n-th event)	Asymmetry; becomes more symmetric with increasing shape parameter
Cauchy	Modelling extreme deviations	Symmetry; heavy tails, mean or variance not defined

A special case is when the monitored feature is calculated from other monitored quality characteristics that do not have a normal distribution. Even if the individual variables have a normal distribution, their combination (e.g. by calculating a ratio, difference, product, or other function) may result in a new variable that does not have a normal distribution. A typical example is the calculation of relative deviations, ratios or composite indices, where the distribution of the resulting variable may become asymmetric.

3.1.2 Natural behaviour of the process over a longer period of time

The application of the above-mentioned standard approaches is also possible in situations where the non-normality is due to the natural behaviour of the process over a longer period of time.

Standard ISO 22514-2 (2017), for example, describes a C3-type process, which is characterised by a non-constant average that varies systematically and by a constant standard deviation. The C3-type process is not in control. In the short run, the data from such a process do not follow a normal distribution. If the process is observed over a longer period of time, the suitable model of the distribution is normal. To analyse the capability of the process, the standard uses the quantile method. However, if this natural behaviour of the process shows up as a trend in the control chart, indicating the operation of special causes of variability that result in the process being out of control, this trend must first be eliminated.

Data non-normality in the long term is not caused only by a change in the mean value of the monitored quality characteristic. Other dynamic effects that disrupt the distribution of data may also be the cause. These include, for example, gradual changes in variance that signal variability in the process without necessarily shifting the mean value, or long-term systematic changes that appear as a trend. Periodic fluctuations associated with time or operating mode can lead to cyclical deviations, while human intervention can result in unobserved changes in process settings. Gradual degradation of technical components and environmental influences beyond the control of the process are further sources of deviation from normality.

As an example, data from the real production process in which tool wear occurs are given. The data does not come from a normal distribution. The observed quality characteristic is the length dimension, specifically the width of the groove for the seal. The control chart for this characteristic shows a decreasing trend until the tool change occurs. Here, tool wear is a variable that changes consistently over time. The operator does not intervene in the process. His only input is the tool change. The machining tool is a milling cutter whose diameter determines the width of the groove. The tool life is 340 pieces produced. The data comes from one machine. Each piece is measured on one CMM machine. The nominal value is 1.975 mm with a tolerance limit of LSL=1.95 mm; USL=2.00 mm.

The histogram in Figure 2 shows a combination of values from different stages of tool wear. It may be the result of a linear trend that is not apparent in the histogram but influences its shape. The trend analysis plot, shown in Figure 3, reveals a decreasing linear trend. In the case of choosing the time series analysis, the variable and model type were first selected, and the residuals were used in the control chart. This is a regression analysis method to remove the trend and obtain residuals that are trend-free. The obtained residuals were used to assess the stability of the process.

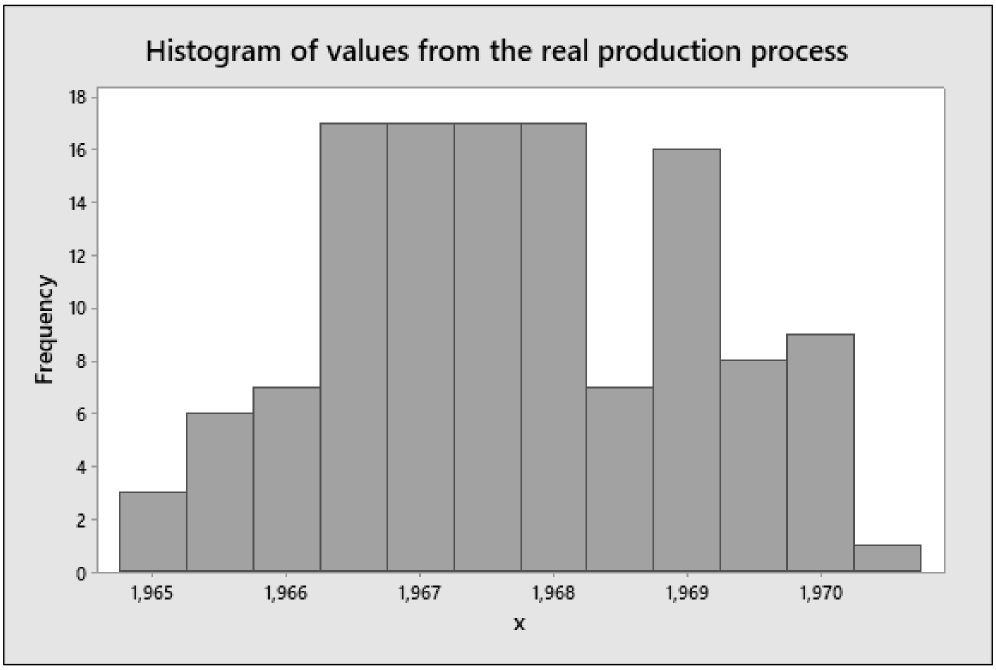

Figure 2 – Histogram of the real data. Source: Author's own work.

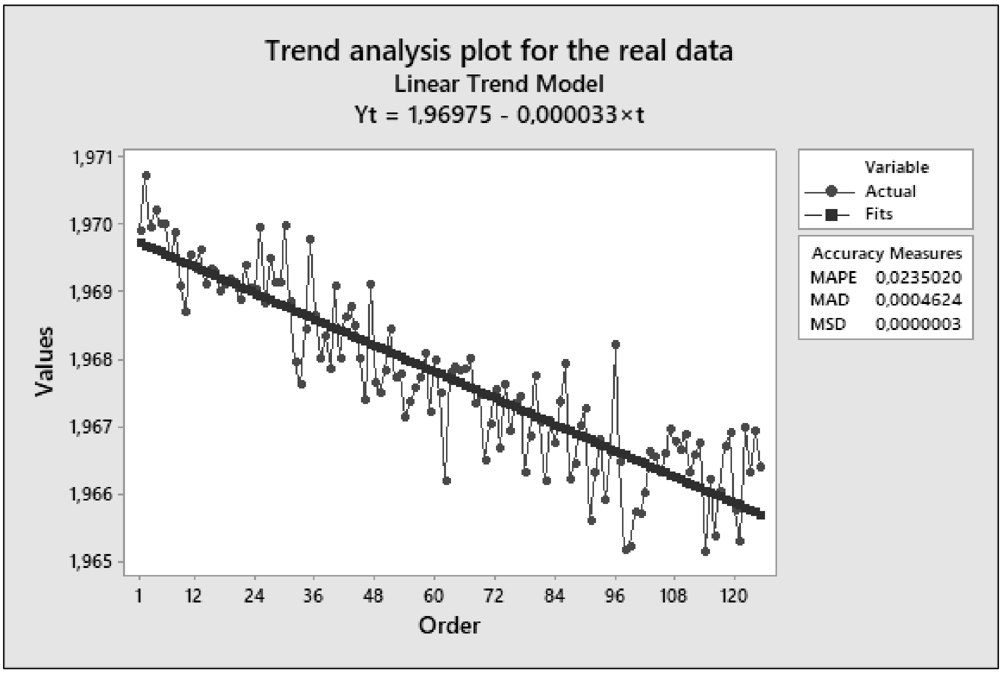

Figure 3 – Trend analysis plot for the real data. Source: Author's own work.

The process capability analysis uses the originally measured values because the specification limits refer to the real values of the quality characteristic, not to the residuals. The customer or technical documentation expects the output to be within the tolerance limits regardless of whether there is a trend in the data. Residuals are useful for assessing whether the process is in control but cannot be used directly to calculate capability indices. For the purpose of process capability analysis, non-normally distributed data were transformed to normally distributed data using the Johnson transformation. The normality of the transformed data was verified using Anderson-Darling test (p-value 0.998). The process was assessed as capable as the capability indices are greater than 1.33.

The procedure based on the use of regression to adjust and remove systematic shifts from process data and subsequent verification of whether the process is under control using residuals is supported by Leone et al. (2011) and Alexopoulos et al. (2023).

Tool wear in manufacturing processes is widely recognised by research studies as a significant cause of disruption to normality, which:

- causes non-standard process signals and affects the probability distribution (Li et al., 2019; Lee et al., 2019; Gai et al., 2022; Cheng et al., 2023; Herrera-Granados et al., 2024; Huang et al., 2024),
- degrades the quality of outputs and leads to process failures (Hao et al., 2017; Lee et al., 2019; Herrera-Granados et al., 2024; Cheng et al., 2023),
- requires advanced monitoring for early detection (Yan et al., 2021; Yang et al., 2022; Herrera-Granados et al., 2024).

Across the studies, tool wear is universally regarded as a natural, expected feature of machining processes. Recent reviews and studies focus on understanding, monitoring, and predicting its progression to minimise negative impacts on quality and productivity. As Munaro et al. (2023) point out, current studies are now working on updates or extensions to process capability analysis or frameworks for tool wear scenarios.

3.2 Data structure

Data structure refers to the way data is organised, grouped, or stored within a dataset. This category reflects the internal organisation of the dataset, which may be influenced, for example, by a combination of different data sources, time periods, production batches, or other segmentation criteria. The resulting structure can substantially affect the statistical properties of the data, including distribution. The nature of this category is that the non-normality arises as a result of the way the data are grouped and presented, not because of the content of the data itself.

3.2.1 Data inhomogeneity and outliers

Inhomogeneity can be caused by data from different sources or by data that are collected at different points in time or include different populations. Data homogeneity refers to data with similar statistical properties, i.e. the mean and variance do not differ significantly between subgroups, and the data have a similar model of distribution. Homogeneity and normality are quite different properties. Data can be homogeneous and exhibit normal or non-normal distributions, just as data can be inhomogeneous and come from different distributions.

The solution is to use advanced probability models that can account for inhomogeneity, such as mixed models. One can also use a stratification, i.e. splitting the data into homogeneous subgroups and then analysing each group of data separately, or use conventional methods (quantile methods, transformation techniques) with outlying observations being identified and removed. Stratification can be performed according to different criteria depending on the nature of the data and the specifics of the production process. Suitable criteria may be period, machine or production equipment, operator, batch, production run, or material type. A major advantage of data stratification is that it provides more detailed information about process behaviour under different conditions. The process should then be proven to be capable under all these conditions. A comparison of the two approaches is shown in Table 2.

Table 2 – Comparison of the properties of the stratification method and the mixed model. Source: Author's own work.

Method	Stratification	Mixed model
Advantages	Simple and intuitive analysis, easy to use in exploratory data analysis	Taking multiple factors into account simultaneously
	No complex modelling required	Allowing modelling of random effects

Method	Stratification	Mixed model
	Obtaining more detailed information about the behaviour of the process under various conditions	Maintaining overall data size
Disadvantages	Risk of information loss when data is split	Need to correctly specify the structure/setting of the model
	Difficult to compare multiple factors at once	Higher demands on knowledge and interpretation
	Interactions between factors are not taken into account, not suitable for more complex data structures	May be sensitive to outliers
		May not always correspond to the monitored data

A special case of inhomogeneity is for outliers that do not fit the probabilistic behaviour of the dataset under investigation. Graphical methods for outlier detection are not much affected by the division into parametric and non-parametric methods. Most tests are flexible enough to be applied to different types of data, regardless of their distribution. The statistical power of a test is the ability of the test to detect the true effect, if any. For example, outlying observations can significantly reduce the statistical power of a test (Cavus et al., 2023) as they increase the variability of the data, which may cause the test to fail to detect this true effect. If the data does not come from a normal distribution, a non-parametric test should be used. For mixed distributions (combination of two or more distributions) reported by Ag-Yi and Aidoo (2022), the Jarque-Bara test is appropriate.

If it is suspected that the data do not come from a normal distribution, it is possible to use a so-called modified Z-score, which is less sensitive to outliers. The median and median absolute deviation (MAD) are used instead of the mean and standard deviation. |Modified Z| values > 3.5 are considered outliers (Mandić-Rajčević and Colosio, 2019; Bae and Ji, 2019). The modified Z-score is calculated according to the relation:

$$Z_{modified} = \frac{0.6745\ (x_i - \tilde{x})}{MAD} \tag{1}$$

where $\tilde{x}$ is median, 0.6745 is a constant ensuring comparability with classical Z-score for normal distribution, MAD is the median absolute deviation, which is calculated $MAD = \tilde{x}\ (x_i - \tilde{x})$, where x_i is a specific value.

Z-scores and modified Z-scores cannot be considered statistical hypothesis tests as they do not have a defined H_0 and H_1, do not return a p-value or make decisions based on a predetermined significance level, but can be part of hypothesis testing and a useful tool for outlier decision making.

For a data that does not come from a normal distribution, a graphical method supplemented by quantification using modified Z-scores is the appropriate procedure. Similarly, it is possible to try to transform the data to approximate a normal distribution and then apply the procedure to the normal data as part of the process capability analysis.

The identification of outliers must be followed by an analysis of their causes. Outlying observations can only be excluded from the dataset if they are proven to be due measurement of recording error, and also if an external effect outside the standard process is proven, e.g. machine failure.

3.2.2 Higher frequency of values near the limit value

Similarly, the capability analysis can be continued if there are many values close to the limit value, if this is a property inherent in the process. The non-normal distribution will be known, and the behaviour of the process will be predictable. A higher concentration of values around the lower or upper tolerance limit may be due to the following - production process is continuously adjusted (i.e. maintained within specified tolerances), manufacturing process with one-sided control or a process with a shifted mean, control of strict quality requirements, repeated verification of the monitored characteristic after a certain period of use (e.g. wear phase), measurement system set to acceptability limits or use of adaptive control systems.

Adjusting processes to those values cluster near specification limits or the target value is a well-known cause of non-normality in production process data. This often leads to skewed or bimodal distributions rather than a classic normal curve. Although it is well known in quality engineering that frequent adjustments of the process towards the limits can cause non-normal data distributions, no research papers have been found that directly study or model this effect. Even the search terms like "process adjustment induced non-normality" or "clustering near specification limits," do not return any relevant results. However, studies can be found that focus on the optimal setting of tolerance limits (Yi et al., 2025; Peng and Han, 2024).

As an example, the model of log-normal distribution in Figure 4 is significantly right-skewed, most values are very close to the lower tolerance in this case. High values have a lower frequency. Such a process is one-sided adjustable, with adjustment to the lower tolerance. This type of distribution can occur if the operator or automated system continually adjusts the process to keep the output as close to the lower tolerance as possible, or if the process is naturally shifted towards the lower tolerance. In the case where the tolerance limit is not equal to zero, there is a high risk of non-conforming products occurring below the tolerance.

A typical characteristic monitored in a production processes may be the thickness of the coating layer, where the operator or system can adjust the equipment to make the layers as thin as possible but still within tolerance. Another example might be the length of the overlap or clearance, such as the gap between parts, where the process is set up to ensure that the parts fit tightly.

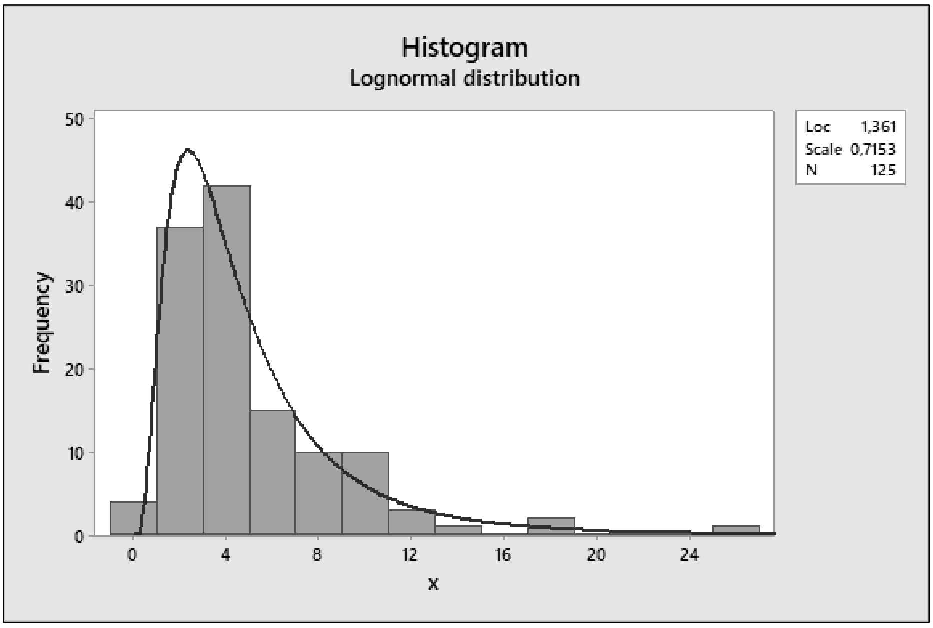

Figure 4 – Histogram for log-normal distribution. Source: Author's own work.

In this case, it is necessary to examine the reasons for the one-sided adjustment or to move the process further away from the tolerance limit.

3.3 Data collection methodology

A data collection methodology is a set of rules, procedures and techniques that determine how data is collected from a process. This category focuses on the temporal, spatial and organisational aspects of data collection that may affect the representativeness of the data. The nature of this category is that non-normality may be the result of an inappropriate choice of methodology that does not match the dynamics of the process or the nature of the characteristic being observed. The methodology of data collection is crucial for the validity of the statistical analysis because even a well-functioning process can be misinterpreted if data are collected in an inappropriate way.

3.3.1 Inappropriate method of data collection

Inappropriate data collection refers to situations where the method, time, place, or conditions of data collection (or its evaluation) do not correspond to the reality of the process, leading to distortion of the dataset. Non-normality caused by inappropriate collection can arise during the process phase, during the data collection itself, or after sorting inspection. These phases with the associated causes of non-normality are shown in Table 3.

Table 3 – Phases of inappropriate data collection and related causes of non-normality. Source: Author's own work.

Process phase	Cause of non-normality
Production process	collecting data only from a selected part of the process

Process phase	Cause of non-normality
	collecting data after intervening in the process
	an unsuitable data collection interval
Data collection	manual sample selection
	preference of values close to the mean
	removal of extreme values
Post-sorting inspection phase	data after sorting inspection
	recording only compliant data (OK products)

The production process phase relates to when and where data is collected within the production process. The data collection phase relates to the methods of selecting or manipulating data, regardless of the production process itself. When collecting data only from a selected part of the process, measurements are taken only at the beginning of a shift or by only one operator. This results in an unrepresentative sample, often with lower variability. Data collection after intervention in the process refers to a situation after machine adjustment or repair. The result then does not reflect the current state of the process. In the case of an inappropriately chosen data collection interval, a non-normality can arise as a result of an inappropriately chosen data collection interval, for example, when, in the case of process periodicity, this interval does not provide information about all process states.

Data after sorting inspection describes a situation where data is collected only after non-compliant products have been discarded. In this case, the distribution will be artificially narrowed with lower dispersion, and normality may no longer be satisfied. When only compliant products are recorded, non-compliant products are not recorded, and part of the distribution is missing from the data file.

The data collection phase is given as an example. This one may reduce the variability of the data or lead to systematic errors if some products are discarded regularly or preferred for certain reasons.

Based on the available research, there are not direct studies that specifically investigate how (sorting) products transforms an originally (normal) distribution into a non-normal one in measurement data. Rabatel et al. (2020) discuss how normalization and variable sorting can improve the robustness and interpretation of multivariate measurement data. Velyka et al. (2021) model sorting and distribution processes in a production environment and analyses the impact of different distribution laws (normal, exponential) on simulation outcomes. The remaining papers focus on sorting algorithms, and their impact on data processing or classification performance, but do not address the specific scenario of sorting products before measurement and its effect on data normality (Jain et al., 2018; Liao et al., 2024; Subramaniam and Chandra Umakantham, 2025).

As an example, data simulation was performed. The histogram for the original data is shown in Figure 5. In contrast, the histogram of data after sorting inspection in Fig. 6 shows the situation how this product sorting before measurement affects the distribution of the data and causes deviations from the normal distribution. This histogram represents the data after sorting inspection, where edge values have been systematically removed, here all values below 40 and above 60. Such interventions in the form of cut-off values lead to an artificial narrowing of the variance but do not reflect the true variability of the process. While all data (original) come from a normal distribution, the normality is violated for data after product sorting.

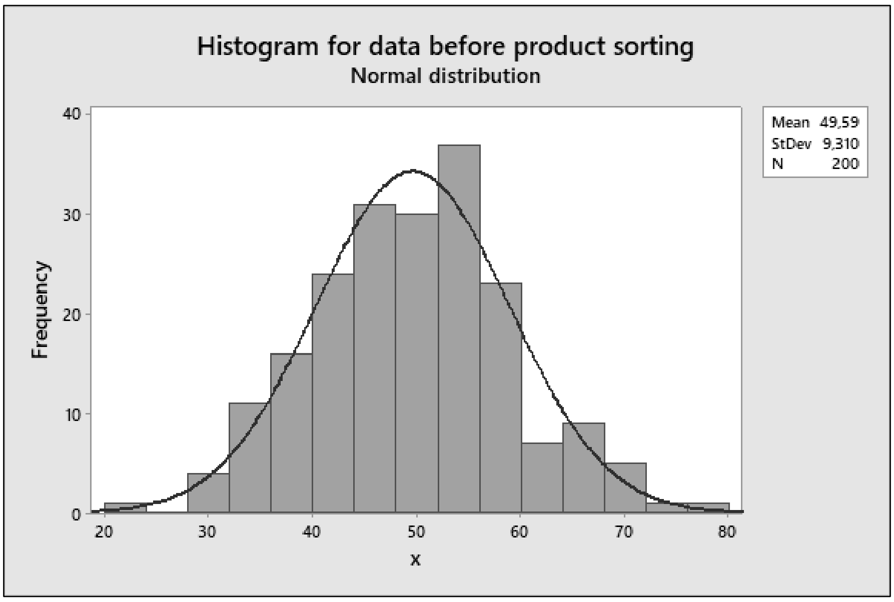

Figure 5 – Histogram of data before product sorting. Source: Author's own work.

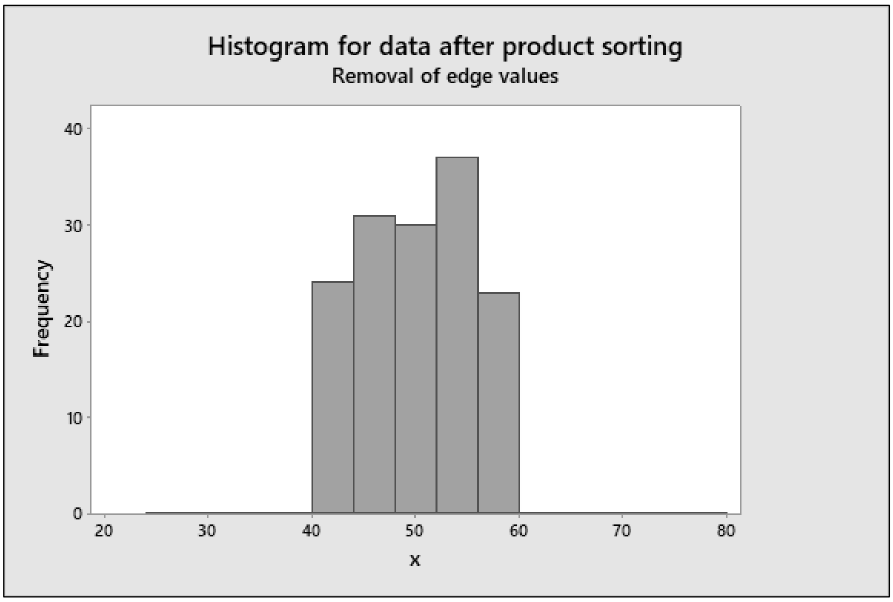

Figure 6 – Histogram of data after product sorting. Source: Author's own work.

Distortion of distribution can also occur when some values are preferred, e.g. values close to the mean. There may be a significant concentration around the middle, with the outlying values significantly less represented or completely absent. This type of distortion can lead to the mistaken judgment that the process seems to be stable and has low variability, when in fact this is not the case.

The following is recommended to prevent systematic distortion of data:

- introduction of random or systematic sampling helps to ensure the representativeness of the data and eliminate human judgement,
- replacing the human factor with automated measuring systems that record data without operator intervention,
- introduction of blind sorting or measurements where the identification of the sample is unknown to avoid biasing the results,
- keeping a record of who performed the sorting and how, including time and conditions, which can help to retrospectively identify sources of distortion.

3.3.2 Sample size

In the context of non-normality, it is also necessary to mention the issue of the sample. For the process capability analysis, at least 125 values (25 subgroups of size 5) are required. There may be a different size of subgroups, but the total number of values should not be less than 125 (AIAG, 2005). If the sample size is small, the probability of drawing an incorrect conclusion about the suitable model of distribution increases. The non-normality may be due to the fact that in such an under-represented sample, the estimates of the parameters of the distribution are not accurate, and the statistical tests show less power by making it less likely that the true effect will be detected.

Important criteria in selecting a test are the number of values in the dataset (Demir, 2022), the power of the test, and the sensitivity to deviations from normality. For example, for small samples ($n<50$) is recommended the Shapiro-Wilk test and for larger samples ($n>50$) the D'Agostino-Pearson test (Avram and Marusteri, 2022). Research shows that the Anderson-Darling test is flexible and can be used for a wide range of sample sizes. From 30 values and above, it is considered highly suitable. This test is also applicable to small sample sizes. Exact or simulated critical values are available for small sample sizes, and several studies provide tables or formulas for these cases (Kitani and Murakami, 2024). However, the statistical power of the test - its ability to detect deviations from the hypothesized distribution - is generally lower with very small samples, meaning the test may not reliably identify non-normality or other distributional differences when N is small (Jäntschi and Bolboacă, 2018). Despite this limitation, Razali and Wah (2011) state that the Anderson-Darling test is still considered one of the more powerful goodness-of-fit tests for small samples compared to alternatives like the Kolmogorov-Smirnov test.

As an example of changing the model of distribution, a log-normal distribution with parameters (0.8;1) was simulated and tested. Anderson-Darling test of goodness of fit with normal and log-normal distributions was performed. This change at different samples sizes is shown in Table 4. Even if the data does not come from a normal distribution, with a small sample size, the normality test may conclude that normality is achieved due to its low power.

Table 4 – Anderson-Darling test result for simulated data from log-normal distribution (0.8;1). Source: Author's own work.

Sample size	p-value (N)	Distribution	p-value (log-N)	Distribution
100	<0.005	non-normal	0.076	log-normal
50	<0.005	non-normal	0.765	log-normal
30	<0.005	non-normal	0.697	log-normal
20	<0.005	non-normal	0.694	log-normal
10	0.059	normal	0.200	log-normal

The same results (normality for a sample size of 10 values) were also obtained for the log-normal distribution with parameters (0;1), (1;0.5), (1;1) and (2;0.5).

These simulations are intended to serve as an illustration of the behaviour of selected normality tests as a function of sample size. The results of this simulation do not aspire to be generalized to other data, given that the sensitiveness of the various tests is already well described in the literature.

A conclusion about the suitable model of distribution should never be based on only one statistical test. A combination of tests, graphical visualizations, and an understanding of context are key to correctly interpreting data. It is important not to automatically assume normality for manufacturing process data. It is appropriate to combine tests with visual methods. If the test result is ambiguous or a small sample is available, it is appropriate to consider using non-parametric methods.

3.4 Measurement systems

The measurement systems category of causes of normality violation deals with the technical, environmental and human aspects of the measurement process. The nature of this category is that non-normality may be caused by the characteristics of the measurement equipment, the measurement conditions or the way the measurement is performed. This category therefore requires systematic monitoring and validation of measurement systems to ensure the consistency and accuracy of the data obtained. The category of measurement systems includes these potential causes of data non-normality:

- technical characteristics of the measuring equipment,
- changes in measurement conditions,

- measurement errors caused by human factors.

Very few studies have been found that examine how data non-normality can arise with the contribution of the measurement system and how this affects further analyses. For example, Cabral et al. (2020) and Arellano-Valle et al. (2020) present advanced models for modelling measurement errors with non-normal distributions. Spicker et al. (2021) introduce a nonparametric method to correct for measurement error without assuming normality.

Data non-normality can be caused by several reasons. Most of these causes can be detected and subsequently eliminated during the measurement system analysis (MSA) that precedes the statistical process control assessment, normality verification, and process capability analysis.

3.4.1 Technical characteristics of the measuring equipment

The causes associated with this area are defined as follows:

- combination of two or more measuring systems,
- limited resolution of the measuring system,
- wear and tear of the measuring system,
- measurement equipment failures,
- incorrect calibration of the measuring system,
- rounding off.

A combination of two or more measuring systems

In a production process, the same characteristic can be measured by two different devices (e.g. newer and older versions) that have different characteristics, e.g. accuracy, calibration, etc. Measurements may be taken at different workstations or on different shifts. The result is a mixture of two distributions.

Recommendations: standardisation of measuring equipment (use of one or more of the same type), introduction of a uniform measurement procedure, regular calibration and comparison of results between measuring equipment, e.g. cross-check method; keeping records of which equipment has been used for a given measurement.

Limited resolution of the measuring system

The measuring equipment used has a low resolution, e.g. it only measures whole units. The cause may be, for example, an analogue display or a digital step. The consequence is loss of detail, artificial grouping of values and reduced sensitivity.

Recommendation: using a measuring device with higher resolution (e.g. instead of rounding to 0.5, measure to 0.1 or 0.01), calibrate the measuring device and thereby ensure that the rounding is consistent and predictable. If possible, a good approach is to keep the unrounded values.

The limited resolution can be also compensated statistically. It depends on what type of analysis the data is intended for. If it is known that the values have been rounded, jittering, i.e. adding a small amount of random noise, can be used. The use of this approach is mainly used to improve the analysis or visualization of the data. The addition of random noise helps to distinguish individual values that would otherwise be "inflated" to the same value due to rounding. Jittering avoids overlapping points and allows a better perception of the distribution of the data, but care must be taken to ensure that the added noise is small enough not to affect the interpretation of the data itself (Ropinski et al., 2021).

Wear and tear of the measuring system

Over time, wear and tear on the measuring equipment, e.g. its mechanical parts, leads to drift in the results.

Recommendations: establish a maintenance and replacement plan for equipment, perform regular calibration, monitor trends in measurements, use control samples to verify accuracy of measurements

Measurement equipment failures

In a production environment, sudden failures and interruptions can occur for various reasons, causing extreme values or random errors. Possible causes include sensor failures, loss of communication between the measuring device and the data acquisition system, faulty software, mechanical damage or manual intervention in the measurement.

Recommendations: introduction of automatic data consistency checking, regular inspection and diagnostics of the equipment, recording and analysis of error messages; introduction of alarms if the value exceeds the physically possible range; identification and analysis of outliers and their removal if they are confirmed as errors.

Incorrect calibration of the measurement system

Incorrect calibration leads to distorted data. The causes of incorrect calibration can be various, e.g. use of a wrong reference standard, mixing up of units, incorrect setting of the measuring range, change of software without subsequent recalibration, incorrect calculation of the correction factor or its absence.

Recommendations: establish a calibration plan, use calibration standards and reference materials, perform check measurements on known samples after each calibration, document and track calibration results, monitor long-term trends in measurements.

Rounding-off

Rounding the values not only causes a loss of resolution but also creates a higher frequency of occurrence of certain values, and the original continuous variable starts to behave like a discrete variable. By rounding, the data loses its natural variability.

Recommendations: check measurement device settings (increase resolution, disable automatic rounding), record original unrounded values, take rounding into account when interpreting results, use measurement device with higher accuracy.

3.4.2 Change of measurement conditions

This situation is typically characterized by a shift of part of the data, which causes asymmetry. Measurements can take place under different conditions, e.g. different temperatures, humidity, vibrations, etc. Measurements can be performed by different operators or on different shifts. Other variations may include the influence of external factors (unstable power supply, electromagnetic interference, etc.) or insufficient stabilization of the measured component, e.g. after heating.

Recommendations: introduction of environmental control (stable conditions), measurement and recording of conditions at each measurement, analysis of the effect of conditions on measurements, introduction of control samples (reference part measurements).

3.4.3 Measurement errors caused by human factors

These errors most often occur when an operator makes a mistake when reading a value or incorrectly records a measured value. Human error can be caused by a variety of factors - fatigue, inattention, stress, lack of training, improper use of measurement equipment, misinterpretation of results, or subjective estimation instead of accurate measurement. These errors are often unpredictable, which is why it is important to introduce standardised procedures, use automated systems and carry out regular training.

Recommendations: implement training and standard operating procedures, use automated measurements, perform data entry checks.

4 DISCUSSION ON PROCESS CAPABILITY ANALYSIS

The different categories of causes of data non-normality, analysed in the previous chapter, also differ in the stage at which process capability analysis can be undertaken. In cases where the non-normality is due to an inherent property of the observed characteristics or process under study, the process capability analysis can proceed by transforming the data to a normal distribution before calculating the capability indices, or by applying modified quantile-based capability indices. Non-normality due to data structure usually indicates that the data are not homogeneous or representative. In such cases, it is not appropriate to proceed with the process capability analysis without first modifying the dataset. If outliers are identified, they should be analyses and excluded from the dataset only if they are clear errors. If the non-normality is due to an inappropriate data collection methodology, the data collection must be repeated. Only after the methodological issues have been corrected and a new dataset has been obtained can a valid process capability analysis be carried out. The normality related to the measurement system deficiencies should be detected already in the phase preceding the process capability analysis, namely the measurement system analysis. If the MSA is performed correctly, most of the reported causes in this category should be identified.

5 CONCLUSION

Violation of the data normality assumption is a significant problem in process capability analysis that can fundamentally affect the accuracy and objectivity of the results. This paper has systematically identified and analysed the main causes of data non-normality in the context of manufacturing processes, highlighting that non-normality is not always the result of random or special causes, but often arises from natural process behaviour, characteristics of the measured variables or deficiencies in the measurement systems.

Research has shown that the causes of non-normality can be divided into several categories. Each of these categories has specific implications for the suitable model of distribution and requires a different approach to analysing the capability. For example, in the case of an intrinsic property of the observed quality characteristic, quantile methods or transformation techniques can be applied, whereas for non-normality caused by product sorting, it is necessary to first remove systematic bias from the data.

Particular attention was paid to the effect of instrument wear, which proved to be a significant factor disturbing the normality of the data. The results of the literature search confirm that wear leads to systematic trends that need to be identified prior to the capability analysis itself. It has also been shown that the causes of non-normality related to higher frequency of values around the limit value and data related to product sorting before and after measurement have not received sufficient attention in research articles.

Another important finding is the effect of sample size on the results of normality tests. Small samples can lead to incorrect conclusions about normality, whereas larger samples have higher test power and allow more accurate identification of non-normality. Therefore, it is essential to combine statistical tests with graphical methods and always consider the context of the data.

One of the main contributions of this study is the systematic mapping and categorisation of the causes of data non-normality in manufacturing processes, which have not been comprehensively described in the literature in one place. While most available studies focus on specific types of distributions or the design of alternative capability indices, this paper provides a comprehensive overview of the causes that lead to violations of the normality assumption, including their practical manifestations, implications, and recommended solutions. This synthesis is based not only on an extensive search of research sources, but also on the author's practical experience in manufacturing organisations. The result is a clear framework that can serve as a guide for quality professionals in identifying and correcting non-normality in data.

In conclusion, non-normality cause analysis should be an integral part of the capability analysis process, or a phase that should precede the process capability analysis. Only a thorough understanding of the origin of the non-normality allows to choose an appropriate analytical approach and to ensure reliable results.

Determining the cause of the non-normality is the key information for further proceeding with the process capability analysis. Only in case where the non-normality is an inherent feature of the observed quality characteristic or process being analysed can it be continued. In other cases, the causes of the non-normality need to be removed and new data needs to be collected.

This paper provides a practical framework for identifying and analysing the causes of non-normality that can be used in both academic research and industrial practice. Future research should focus on developing methods for their automatic detection and correction.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest. The funders had no role in the design of the study, in the collection, analyses, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.

DISCLOSURE OF ARTIFICIAL INTELLIGENCE ASSISTANCE

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