Confidence Intervals for the Mean in Selecting an Appropriate Time-Dependent Distribution Model for Processes with Non-Normal Instantaneous Distributions

DOI: 10.12776/qip.v29i2.2183

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Received: 12-05-2025 Accepted: 19-06-2025 Published: 31-07-2025

ABSTRACT

Purpose: This paper proposes using confidence intervals for the mean to select a suitable time-dependent distribution model for a process with non-normal instantaneous distributions.

Methodology/Approach: The approach examines a studied characteristic by analysing its distribution, location, dispersion, and shape, all of which are time functions. The values of the characteristic are determined by sampling from the process flow. A time-dependent distribution model represents the process.

Findings: The paper explains how to utilise confidence intervals for the mean when selecting an appropriate time-dependent distribution model for processes with non-normal instantaneous distributions.

Research Limitation/Implication: The methods described in this document pertain exclusively to continuous quality characteristics and can be applied to analyse processes across various industrial and economic sectors. The presented procedures are appropriate for use when the instantaneous distributions are non-normal.

Originality/Value of paper: Confidence intervals for the mean can improve decision-making when selecting a suitable time-dependent distribution model.

Category: Research paper

Keywords: confidence interval for the mean; time-dependent distribution model; random sample; non-normal distribution

Research Areas: Quality Engineering

1 INTRODUCTION

A crucial aspect of understanding a process is identifying its distribution and evaluating its capability or performance. Time-dependent distribution models describe how a characteristic evolves over time. This article builds on "Terek, 2025," where we discussed using confidence intervals for the mean and variance to select an appropriate time-dependent distribution model when all instantaneous distributions are normal. In this paper, we examine the application of confidence intervals for the mean in situations where the instantaneous distributions are non-normal.

Most of the literature concerning the performance of the processes assumes that the process is in a state of statistical control, with stationary, normally distributed processes. Reliable predictions of process performance can only be achieved when the process is stable, meaning its distribution parameters remain unchanged over time. A process with only common causes of variation is said to be in statistical control (in an in-control state) or a stable process. A process affected by both common and assignable causes is an out-of-control process (in an out-of-control state) or an unstable process. Processes will often operate in the in-control state for relatively long periods. However, no process is truly stable forever, and, eventually, assignable causes will occur, seemingly at random, resulting in a shift to an out-of-control state where a larger proportion of the process output does not conform to requirements. A major objective of statistical process control is to quickly detect the occurrence of assignable causes of process shifts so that investigation of the process and corrective action to return the process to an in-control state may be undertaken before many nonconforming units are manufactured (Montgomery, 2020, p. 189). Unfortunately, in many processes, the assumption that the process is in a state of statistical control and is normally distributed with constant parameters, which can change only by the influence of known assignable causes, may not be met. Oakland and Oakland (2019, pp. 316-317) state that numerous potential assignable causes exist for out-of-control processes. Providing a complete list of assignable causes for a specific process is practically impossible. When the process is out of control, it can often be difficult to identify the assignable causes responsible for it. Consequently, we cannot take corrective actions to bring the process to an in-control state. Additionally, the common causes may change over time; thus, the process distribution may change, even without assignable causes (Oakland and Oakland, 2019, p. 317; Terek, 2025). On the other hand, we can identify specific assignable causes, such as regular fluctuations in environmental conditions like changes in humidity and temperature. These fluctuations can lead to cyclical or trending changes in the monitored characteristics. However, reducing these fluctuations may be technologically impossible or economically inappropriate.

Effective process control and improvement must be based on careful analysis. Therefore, it is useful to analyse the process behaviour over time and to recognise the suitable time-dependent distribution model. An appropriate method of process performance assessment and statistical process control can only be chosen based on the results of such analysis.

The capability and performance indices are one of the essential tools for measuring process performance (Terek and Hrnčiarová, 2004; Pearn and Kotz, 2006; Costa et al., 2019; Tošenovský and Tošenovský, 2019; Montgomery, 2020; Benková et al., 2024; ISO/DIS 22514-2, 2024). The capability indices may only be used if the process is stable. If the stability cannot or should not be evaluated, or if the process is explicitly unstable, the performance indices are used. The methods to calculate these indices depend on the time-dependent distribution model applied to the process. ISO/DIS 22514-2, 2024 lists various methods for calculating location and dispersion estimates to compute process capability and performance indices. It specifies which methods are suitable for different time-dependent distribution models of the process (ISO/DIS 22514-2, 2024, Table 5). Therefore, accurately estimating the time-dependent distribution model for the process is crucial for the right calculation capability and performance indices. Additionally, the type of time-dependent distribution model is an important factor in determining a suitable statistical process control method. For instance, ISO/DIS 11462-1, 2025, specifies on page 33 in Table 9 which control charts are recommended for various time-dependent distribution models.

Typically, significance tests are suggested for identifying a suitable time-dependent distribution model for a process. However, in many instances, significance tests are not as informative as confidence intervals (Agresti et al., 2023, pp. 462-463). Confidence intervals not only help determine if a hypothesis regarding the stability of parameters over time can be rejected, but they also offer a range of plausible values for the population parameters.

This paper will investigate how confidence intervals for the mean can be used to estimate time-dependent distribution models for processes with non-normal instantaneous distributions. We will use simulations to illustrate this concept. Applying the proposed approach to assessing a time-dependent distribution model can lead to more accurate and reliable process characterisation, resulting in better decision-making.

We begin by categorising time-dependent distribution models when the instantaneous distributions are non-normal. Then, we describe how to use the confidence intervals for the mean to determine the type of time-dependent distribution model. Finally, we demonstrate the obtained results through simulations.

2 LITERATURE REVIEW

The instantaneous (short-time) distribution describes the behaviour of the characteristic during a short time interval, typically when a sample is taken from the process. The process distribution when a process is observed continuously over a longer period is called the resulting distribution. This distribution is described by a time-dependent model that reflects the instantaneous distribution of the characteristic being followed and the changes in location, dispersion, and shape parameters during the time interval of process observation. The resulting distribution can be represented by the entire dataset or all subgroups obtained during the process observation period (ISO/DIS 22514-2, 2024; Terek, 2025).

Eight different time-dependent distribution models are known. Terek (2025) states their classification (see also ISO/DIS 22514-2, 2024; Jarošová and Noskievičová, 2015).

The models A1, B, C1, and C2 are analysed in Terek (2025). This paper will focus on models that do not assume a normal distribution for the instantaneous distributions. Specifically, we will examine the following models:

- Model A2: This model features non-normal but unimodal instantaneous distributions with constant location and dispersion.
- Model C3: Characterised by a systematic (trend) change in location, this model has unimodal instantaneous distributions and the resulting distribution of any shape.
- Model C4: In this model, there are systematic and random changes in location. Instantaneous and resulting distributions are of any shape.

For models C3 and C4, the cause of the trend may be gradual wear of the tool during turning, grinding, or drilling, etc., but also gradual change in the composition or efficiency of chemical solutions or catalysts, gradual cooling or, conversely, heating of the material, for example, during mechanical processing, etc. At the moment of reconditioning or replacing the tool, using a new solution or batch of material, a sudden change in the data occurs in the opposite direction. Cyclical changes in the characteristic being considered may result from the regulation of process parameters or regular fluctuations in environmental conditions such as temperature and humidity. Reducing this fluctuation may be either technologically impossible or economically disadvantageous in current conditions (Jarošová and Noskievičová, 2015, p. 48; Zgodavová et al., 2020).

- Model D: This model includes systematic and random changes in location and dispersion. Instantaneous and resulting distributions can take any shape.

The process analysis should identify a suitable time-dependent distribution model. Normality tests determine whether a normal distribution can accurately represent a population. Several tests are available for this purpose (Ghasemi and Zahediasl, 2012; Thode, 2002). Suppose the normality assumption is rejected for the instantaneous distributions. In that case, it is advisable to use a median-based test instead of a mean-based one (Median Test) to test that the medians of the populations from which samples are drawn are identical. When samples originate from non-normal distributions, the equality of variances can be assessed using Levene's or Brown-Forsythe's test (Levene's Test, Brown-Forsythe Test).

A histogram can help determine whether the distribution is unimodal or has another shape. For small datasets, histograms can vary significantly based on the number and width of the bins used. Therefore, histograms are more reliable for larger datasets, ideally with a size of 75 to 100 or more (Montgomery and Runger, 2018, p. 137).

3 METHODOLOGY

Suppose we take more random samples from the process flow over a time that covers all potential expected changes. The behaviour of the parameters in instantaneous distributions will be studied based on these samples.

We have written that the instantaneous distribution describes the behaviour of the characteristic during a short time interval, typically when a sample is taken from the process. The population at that time was finite. If we assume that the process remains stable during this interval, it means that the environment and the characteristics of the process exhibit some degree of permanence. While there may be fluctuations in these characteristics and the environment, such fluctuations occur slowly relative to the production speed. Therefore, the finite population existing at a given time interval can be viewed as part of an imaginary, infinite population that exists over time, where the conditions of the process remain constant. As a result, the obtained random sample can be considered a random sample from this infinite population (Giard, 1985, pp. 167-168).

A random sample of size n from an infinite population is selected in such a way that it meets the two following conditions. All units in the sample are drawn from the same population. Each unit is selected independently (Anderson et al., 2020, p. 324). Then, the observations are statistically independent and identically distributed random variables, and the usual statistical inference methods can be used. The sample should consist of units produced simultaneously or as closely together as possible to ensure that all observations are from the same population (probability distribution). Ideally, consecutive units of production should be taken. The independence conditions should be fulfilled so that the units are produced independently. Therefore, the production of each unit can be viewed as the execution of an independent random experiment (Terek, 2025).

We calculate the $(1 - \alpha)100\%$ confidence interval for the mean for each sample. If $\bar{x}$ is the value of the sample mean of a random sample of size n from a normal population with a known variance σ^2, then,

$$\bar{x} - z_{1-\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}} \leq \mu \leq \bar{x} + z_{1-\frac{\alpha}{2}} \frac{\sigma}{\sqrt{n}} \quad (1)$$

where

$z_{1-\frac{\alpha}{2}}$ is $(1 - \frac{\alpha}{2})100\%$ quantile of the standard normal distribution,

$\sigma = \sqrt{\sigma^2}$ – standard deviation, is the (1 – α)100% confidence interval for the mean. According to the central limit theorem, these results can also apply to random samples from non-normal populations, provided that the sample size n is sufficiently large; specifically, n should be at least 30. In that case, we may also substitute for σ the value of the sample standard deviation s, where

$$s = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}\left(x_j - \bar{x}\right)^2}$$

(Miller and Miller, 2014, p. 320; Terek, 2017a; Terek, 2017b; Terek, 2019).

We will assume the large samples of the same size n ($n \geq 30$), and the same confidence level (1 – α) for all confidence intervals for the mean, which are calculated using the following formula:

$$\bar{x} - z_{1-\frac{\alpha}{2}}\frac{s}{\sqrt{n}} \leq \mu \leq \bar{x} + z_{1-\frac{\alpha}{2}}\frac{s}{\sqrt{n}} \tag{2}$$

Let's consider two independent random samples of size n, drawn from two populations with means μ_1 and μ_2. We will calculate confidence intervals (2) for μ_1 and μ_2 based on these samples. In Terek, 2025, it is proven that if the two intervals (2) do not overlap or just touch each other in the test:

H_0: $\mu_1 = \mu_2$ (3)

H_1: $\mu_1 \neq \mu_2$

Based on the same two samples at the significance level, we reject H_0 in favour of H_1.

We draw several independent random samples from the process flow over a period that captures all potential expected changes. Suppose corresponding instantaneous distributions are non-normal. For each sample, we calculate the corresponding confidence interval for the mean, using the same confidence level (1 – α) and sample size n. We can draw specific conclusions from the time series diagram of these confidence intervals. If at least two confidence intervals do not overlap or merely touch, we can conclude that the process mean changes over time. However, if all the confidence intervals overlap, it does not necessarily indicate that the mean is not changing over time. We should consider performing tests for pairs of means (3) or using a median test in such cases. The time series diagram of confidence intervals can also reveal trends or cycles in the evolution of the means of the instantaneous distributions, if they exist.

If the instantaneous distribution is non-normal, we cannot calculate the corresponding confidence interval for the variance. The margin of error in a confidence interval (2) is defined using the following formula:

$$z_{1-\frac{\alpha}{2}}\frac{s}{\sqrt{n}} \tag{4}$$

The confidence level $(1-\alpha)$ and sample size n are constant across all confidence intervals in the time series of confidence intervals for the mean. As a result, the width of the confidence intervals is proportional to the sample standard deviation, s. If the sample standard deviation is used to estimate the population standard deviation σ, the width of the confidence interval offers an initial insight into the evolution of the standard deviation of the instantaneous distributions. A wider confidence interval indicates a greater population standard deviation. By comparing the confidence interval widths, we can evaluate the stability of standard deviations and identify any trends or cycles in their evolution, if they exist. It is important to note that the sample standard deviation is not an unbiased estimator of the population standard deviation, even if the population follows a normal distribution. Furthermore, the sample standard deviation is only a point estimator. Therefore, the procedure mentioned should be viewed as an exploratory analysis only. For confirmatory analysis, it is advisable to use Levene's or Brown-Forsythe's test to assess the equality of variances.

The following procedure can be used: More random samples will be drawn from the process flow over a time that covers all potential expected changes. Suppose the normality of the instantaneous distribution was rejected based on the first sample, let's say with a size of $n = 30$. From this, it can be concluded that all subsequent instantaneous distributions will also follow a non-normal distribution. It is generally accepted that a process with a non-normal distribution will not spontaneously transform into a normal distribution without some form of external change or intervention. Then, increasing the sample size to $n = 75$ by adding 45 observations is recommended, and continuing the sampling with this larger size to determine whether the instantaneous distributions are unimodal or of any shape, using histograms. Afterwards, the calculation of the confidence intervals for the mean and the diagram drawing of the time series for these confidence intervals are realised. Lastly, based on all samples collected during the observation period, we will analyse the resulting distribution using a histogram to determine if it is unimodal or has a different shape.

4 SIMULATION EXPERIMENTS

In this paper, we only examine cases where we cannot accept the normality of the instantaneous distributions. This includes models A2, C3, C4, and D. As in Terek (2025), we will consider one characteristic: the dimension of a product, which will be measured in millimetres (mm).

In situation A2, we model all instantaneous distributions as the distributions of the random variable $X = 99.96 + (1/30)\,W$, where W follows a Weibull distribution with parameters $\lambda = 1,\ k = 1.5$. The distribution of X is continuous, unimodal, and skewed to the right. We generated ten random samples, each containing 75 observations from this distribution. Next, we calculated a 95% confidence interval for the mean for each sample. We have included a diagram displaying all 750 observations (Figure 1 on the left) and a time series diagram of the confidence intervals for the mean (Figure 1 on the right).

In situation A2, the confidence intervals diagram (see Figure 1 on the right) shows that all intervals overlap. This suggests that we have not proven the differences in means of the instantaneous distributions; however, it does not necessarily imply that the means are equal. In such cases, it is advisable to conduct test (3) for the pairs of means or a test based on the median. The comparison of the widths of the confidence intervals suggests that there may not be a difference in the standard deviations of the instantaneous distributions. This result of an exploratory analysis should be confirmed using Levene's or Brown-Forsythe's test.

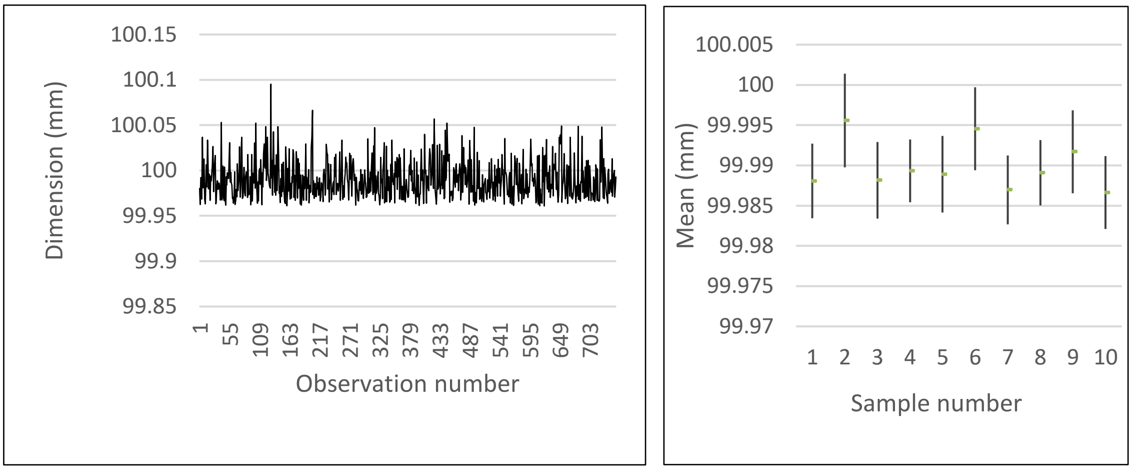


Figure 1 – A2: Observations and confidence intervals for the mean

In model scenario C3, we represent all instantaneous distributions as the distributions of the random variable $X = a + (1/15)W$, where W follows a Weibull distribution with parameters $\lambda = 1$ and $k = 1.5$. The value of a in this expression is 99.96 for the first sample, and increases regularly by 0.01 with each subsequent sample. The distributions of X are continuous, unimodal, and skewed to the right. We generated 10 random samples from these distributions, each comprising 75 observations. We calculated a 95% confidence interval for the mean for each sample. We have included a diagram displaying 750 observations (Figure 2 on the left) and a time series diagram of the calculated confidence intervals for the mean (Figure 2 on the right).

In Case C3, the confidence intervals diagram for the mean shows non-overlapping intervals. This indicates that we have statistical evidence that the mean varies over time. In addition, the diagram very clearly shows an upward trend in the means. The comparison of the widths of the confidence intervals suggests that there may not be a difference in the standard deviations of the instantaneous distributions. As with Case A2, this result should be confirmed using Levene's or Brown-Forsythe's test.

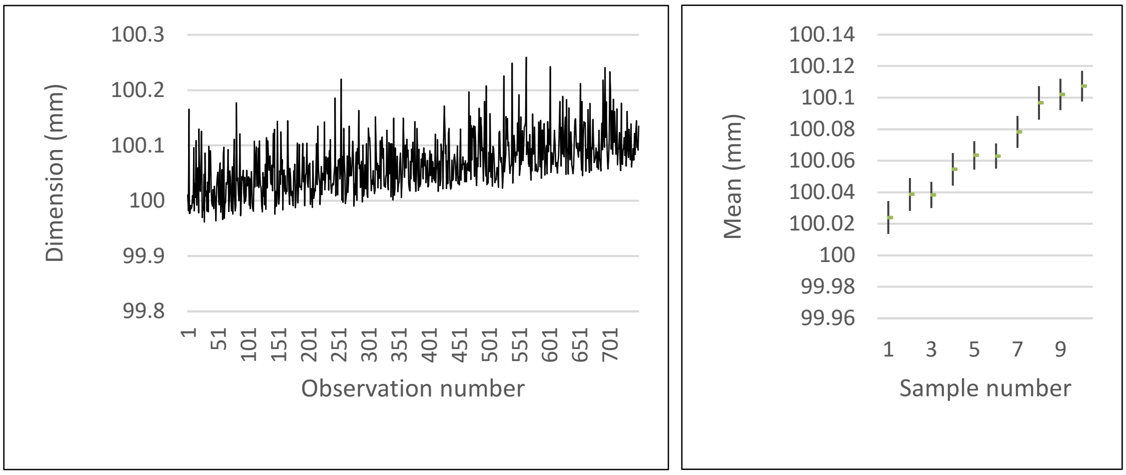
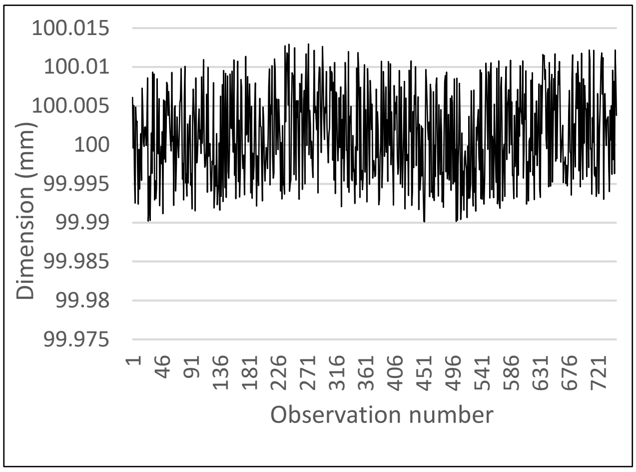


Figure 2 – C3: Observations and confidence intervals for the mean

In situation C4, we assume that all instantaneous distributions are continuous uniform, with a lower limit that increases regularly from 99.99 to 99.993 in increments of 0.001. Following this, the lower limit decreases from 99.993 to 99.99 in increments of 0.001. Finally, the lower limit increases from 99.99 to 99.993 in increments of 0.001. The range of the uniform distribution remains constant at 0.02 throughout these changes. We generated 10 random samples from these distributions, each comprising 75 observations. We calculated a 95% confidence interval for the mean for each sample. We have included a diagram displaying 750 observations (Figure 3 on the left) and a time series diagram of the calculated confidence intervals for the mean (Figure 3 on the right).

In situation C4, the confidence interval diagram for the mean shows non-overlapping intervals. This indicates that we have obtained statistical evidence that the mean changes over time. Additionally, the diagram clearly illustrates cyclical variations in the means. The comparison of the widths of the confidence intervals suggests, similar to what we observed in models A2 and C3, that there may not be significant differences in the standard deviations of the instantaneous distributions. This should be confirmed using Levene's or Brown-Forsythe's test.



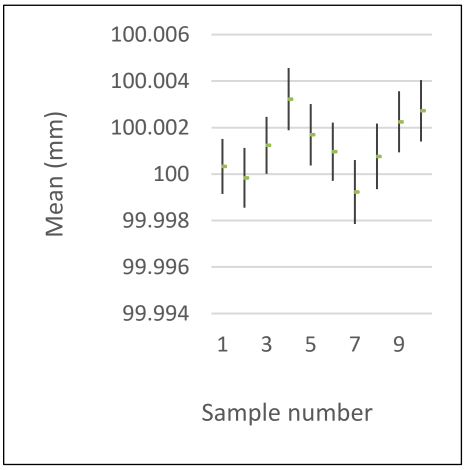
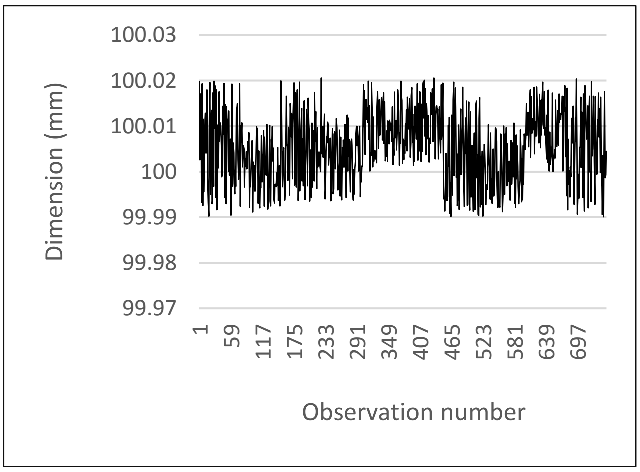


Figure 3 – C4: Observations and confidence intervals for the mean

In model scenario D, we assume all distributions are continuous uniform, with lower limits between 99.990 and 100.001 mm and the range between 0.01 and 0.031 mm. We generated 10 random samples from these distributions, each comprising 75 observations. We calculated a 95% confidence interval for the mean for each sample. We have included a diagram displaying the 750 observations (Figure 4 on the left) and a time series diagram of the calculated confidence intervals for the mean (Figure 4 on the right).



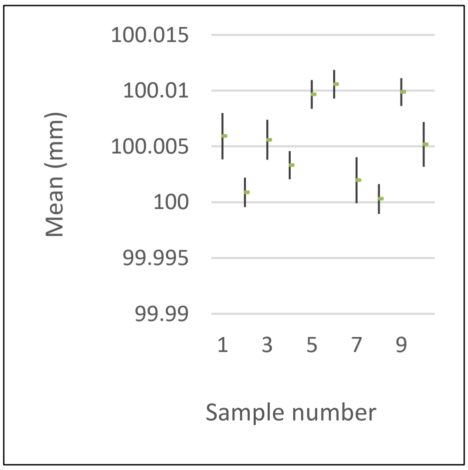


Figure 4 – D: Observations and confidence intervals for the mean

In Case D, the confidence intervals diagram for the mean contains non-overlapping intervals. This indicates statistical evidence that the mean varies over time. Furthermore, comparing the widths of confidence intervals may indicate differences in the standard deviations of the instantaneous distributions. This hypothesis should be verified using Levene's or Brown-Forsythe's test.

In all the models mentioned, histograms can be created from the sample data to assess whether the instantaneous distributions are unimodal or display a different shape. This method also applies to the overall distribution, where data from all samples can be used to create a histogram.

5 CONCLUSION

The paper discusses using confidence intervals for the mean to estimate a time-dependent distribution model for the process. The time-dependent distribution model used for the process determines the method for calculating capability and performance indices. Additionally, it is an important factor in selecting an appropriate statistical process control method.

We suppose that more random samples will be drawn from the process flow over a time that covers all potential expected changes, and that all instantaneous distributions are non-normal. For each sample, the confidence interval for the mean is calculated, with all confidence intervals sharing the same confidence level and sample size. Then, a time series diagram of these confidence intervals for the mean is drawn. It is known (Terek, 2025) that if, under defined conditions, at least two confidence intervals for the mean (2) do not overlap or just touch each other, we can conclude that the process's mean changes over time. These diagrams can also assist in identifying trends or cycles in the evolution of the mean, if they exist. However, if all the confidence intervals overlap, it does not necessarily indicate that the mean is not changing. We should consider performing tests for pairs of means (3) or using a median test in these situations.

The width of the confidence intervals for the mean (2) is influenced by the sample standard deviation s, which estimates the population standard deviation σ. These widths can indicate the stability of the standard deviation in instantaneous distributions (when the confidence levels and sample sizes are the same across all confidence intervals). Additionally, it can help identify the trends or cycles in the evolution of the standard deviation, if they exist. However, since the sample standard deviation is not an unbiased estimator of the population standard deviation and is only a point estimator, this approach should be considered only exploratory. Conducting either Levene's or Brown-Forsythe's test is recommended to confirm any findings.

If the assumption of a normal distribution for the instantaneous distribution is rejected, we recommend using a sample size of $n = 75$ to analyse it and determine whether it is unimodal or has a different shape. This sample will also be used to calculate the confidence interval for the mean. A histogram with the data from all samples can be used to examine the overall distribution.

We have simulated the process behaviours according to the time-dependent distribution models A2, C3, C4, and D. The created time series diagrams of confidence intervals for the mean illustrate their usefulness in assessing the stability of the mean of instantaneous distributions over time and for identifying any trends or cycles in the mean's progression (see Figures 2 and 3). They also serve as valuable tools for exploratory analysis of how the standard deviation of the instantaneous distributions evolves.

The results of this study are theoretically intriguing, as they utilise a new methodology for estimating a time-dependent distribution model. This approach has practical implications, as it offers a quick and informative overview of the most suitable model. The confidence intervals for both the mean and variance can be used in confirmatory analysis when the instantaneous distributions follow a normal distribution (Terek, 2025). This allows for mapping movements in the mean and variance while identifying existing trends and cycles in these parameters. The understanding of the relationship between the overlap of confidence intervals and certain hypothesis tests can also be beneficial in other contexts.

This paper specifically examines the use of confidence intervals for the mean when the instantaneous distributions do not follow a normal distribution. One significant advantage of confidence intervals, compared to hypothesis testing, is their ability to identify existing trends and cycles. Additionally, unlike hypothesis tests, confidence intervals provide a range of plausible values for population parameters. Confidence intervals for the mean are also beneficial in exploratory analysis. Given the same sample size and confidence level, they offer insights into the evolution of variance. The capacity of confidence intervals to visually synthesise the overall situation is noteworthy, reinforced by the diagrams presented.

Overall, confidence intervals in this context can be understood as a supplementary tool to relevant statistical tests. They can even replace such tests when the intervals do not overlap. In contrast to hypothesis testing, confidence intervals provide additional advantages. By employing this approach to estimate a time-dependent distribution model, we can achieve a characterisation of the process that is quicker, more accurate, informative, and reliable, ultimately leading to improved decision-making.

ACKNOWLEDGEMENTS

The author expresses gratitude to the Vysoká škola manažmentu/City University of Seattle for its comprehensive support of his research activities.

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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, analysis, or interpretation of data, in the writing of the manuscript, or in the decision to publish the results.