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Robust yield test for a normal production process

Hamideh Iranmanesh, Mehdi Jabbari Nooghabi, and Abbas Parchamie

ABSTRACT

Testing the performance of a production process is a very serious and important topic in statistical quality control. This article presents a robust yield test to investigate the performance of an industrial production process in the presence of outliers. For this purpose, a new robust estimator of \( S_{pk} \) is introduced to test the production yield for any normal distribution in the presence of various numbers of outliers. Moreover, a Monte Carlo simulation method to estimate the decision-making components is proposed for testing the production yield based on the yield index \( S_{pk} \) by normal data. Meanwhile, this article discusses how well the proposed Monte Carlo method can be used for some non-normal data. Numerical computations of the simulation and real data analyses are provided to explain the proposed method.

KEYWORDS

yield analysis; testing capability; Monte Carlo simulation; outliers; robustness

1. Introduction

Process capability indices (PCIs) have been extensively applied in the industrial processes to evaluate whether the quality of products meets the preset specification limits (SLs). The two most popular indices \( C_p \) and \( C_{pk} \) are introduced as

\[
C_p = \frac{USL - LSL}{6\sigma},
\]

and

\[
C_{pk} = \min \left\{ \frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma} \right\},
\]

where \( LSL \) is the lower SL, \( USL \) is the upper SL, \( \mu \) is the process mean, and \( \sigma \) is the process standard deviation; see Kane (1986). The PCI \( C_p \) measures the process variation related to the preset SLs. The PCI \( C_{pk} \) considers the magnitudes of the process variation as well as the degree of the process centering, which measures the performance of the process based on the production yield. For situations with two-sided specifications in the process capability analysis, \( Yield = P(LSL \leq X \leq USL) \) is a process yield, in which \( X \) is a process quality characteristic. If \( X \) is normally distributed, then the process yield can be exactly defined as

\[
Yield = \Phi((USL - \mu)/\sigma) - \Phi((LSL - \mu)/\sigma),
\]

where \( \Phi \) is the cumulative distribution function of the standard normal distribution; see Pearn and Chuang (2004). Moreover, for a normally distributed process with the fixed \( C_{pk} \), the bounds on the process yield can be obtained as (see Boyles, 1991)

\[
2\Phi(3C_{pk}) - 1 \leq Yield \leq \Phi(3C_{pk}).
\]

It must be noted that the PCI \( C_{pk} \) presents a proximate measurement rather than a precise measurement of the process yield. To acquire a precise measurement, Boyles (1994) proposed the PCI

\[
S_{pk} = \frac{1}{3} \Phi^{-1} \left\{ \frac{1}{2} \Phi \left( \frac{USL - \mu}{\sigma} \right) + \frac{1}{2} \Phi \left( \frac{\mu - LSL}{\sigma} \right) \right\},
\]

(1)

for a normal process, in which \( \Phi^{-1} \) represents the inverse function of \( \Phi \), and there is a one-to-one relationship between the PCI \( S_{pk} \) and the production yield, which can be given by

\[
Yield = 2\Phi(3S_{pk}) - 1.
\]

(2)

For the normal process, the expected number of nonconformities corresponding to a capable process with \( S_{pk} = 1.00 \) will be 2700 parts per million. Therefore, the conventional PCI \( S_{pk} \) is widely proposed in the normal industrial production processes to present a precise measurement of the process yield. The exactitude of the natural estimator (NE) of \( S_{pk} \)
was checked in Pearn and Chuang (2004) based on the simulation method to acquire the relative mean square error and relative bias for several quality requirements. Pearn, Wang, and Yen (2006) developed a generalized yield index, and they obtained a lower confidence bound for the production yield. The relationship between the distribution of the overall index $S_{pk}^T$ and process parameters was investigated in Pearn and Cheng (2010). A fuzzy-based procedure was presented in Afshari, Sadeghpour Gildeh, and Ahmadi Nadi (2020) to evaluate the overall yield with the presence of a determined degree of vagueness.

In general, using PCIs is necessary to measure how much of the process productions meet the preset capability requirement. Since outliers mask the attributable causes of the variation, one may face unreliable results on using the PCIs. Robust time series methods were considered in Prasad and Bramorski (1998) to define new sets of PCIs for a wide range of industrial processes. The second author (Jabbari Nooghabi, 2020) introduced the PCIs based on the parametric model of outliers. The motivation for using a Monte Carlo (MC) technique was discussed in Parchami, Iranmanesh, and Sadeghpour Gildeh (2022) to test the quality of a manufacturing process based on Yongting's index. Iranmanesh, Parchami, and Sadeghpour Gildeh (2022) proposed the statistical fuzzy quality test for analyzing the manufacturing process based on fuzzy SLs. The MC simulation method was presented in Iranmanesh, Parchami, and Jabbari Nooghabi (2023) to test the quality of a production process based on the popular capability index $C_{pk}$. However, the presence of outliers might have a serious effect on statistical analyses and decisions in testing the performance of the production process.

Therefore, the Bootstrap technique for statistical inference is used to estimate the decision-making component in testing the capability of the process in the presence of outliers.

The aim of the present study is to introduce a new robust estimator of $S_{pk}$ to test the process performance based on the production yield. For this aim, the MC technique is used to estimate the components of the decision-making for testing the process yield based on the PCI $S_{pk}$. A simulation study as well as a real data example is provided to show the performance of testing the production yield. This article is structured as follows. Section 2 introduces the non-robust and robust estimators of $S_{pk}$. Section 3 provides a comparison study between the proposed robust estimator and different estimators of $S_{pk}$. Section 4 incorporates hypotheses testing for analyzing the performance of the production process on the basis of the proposed robust estimator of $S_{pk}$. Section 5 proposes the MC simulation procedure to estimate the decision-making components in testing the production yield based on the yield index $S_{pk}$. The proposed MC simulation method is also extended based on some non-normal processes. Numerical and simulation results are presented in Section 6. Section 7 compares the proposed method with different methods. Finally, conclusions and future works are detailed.

### 2. Non-robust and robust estimators

During the last three decades, the statistical term “Outlier” has been discussed in the literature. An outlier is an observation in the distribution of data that swerves so much from the other observed data points (Jabbari Nooghabi, 2020). When a dataset is contaminated with a single or few outliers, we face a serious problem in parameter estimations. In this regard, robust estimation methods can be very applicable to investigate the yield/capability of the process.

Generally, two simple robust estimators of location and scale parameters are the median and the median absolute deviation (MAD), respectively. The MAD is one of the alternatives of the robust estimator of the standard deviation. Therefore, Hampel (1974) defined the MAD as

$$MAD = \text{median} |X_i - M|,$$

where $M$ is the sample median, which is used as a robust estimator of $\mu$. In this study, $1.4826 \times MAD$, which is commonly called the standardized MAD, is considered as a consistent robust estimator of $\sigma$ at the normal distribution (Rousseeuw and Croux 1993).

Also, the simpler but less robust estimator of the scale parameter is the interquartile range (IQR), that can be computed with the IQR function.

**Definition 1.** Let $IQR$ be the difference between the 75th and 25th percentiles of the sample data ($IQR = Q_3 - Q_1$). Then, an IQR-based threshold is defined as follows:

$$\begin{align*}
T_{\text{min}} &= Q_1 - 1.5 \times IQR, \\
T_{\text{max}} &= Q_3 + 1.5 \times IQR,
\end{align*}$$

where $T_{\text{min}}$ and $T_{\text{max}}$ are the minimum and maximum threshold for detecting the outliers. Generally, the data point which lies outside of the interval $[T_{\text{min}}, T_{\text{max}}]$, is considered as an outlier (Yang, Rahardja, and Fränti 2019).
In order to estimate the yield index $S_{pk}$, one can consider the following definition as a non-robust estimator of $S_{pk}$ (see Lee et al. 2002).

**Definition 2.** Let $\bar{X} = \sum_{i=1}^{n} X_i / n$ and $S^2 = \sum_{i=1}^{n} (X_i - \bar{X})^2 / (n - 1)$ be the sample mean and the sample standard deviation, respectively. Then, the NE of $S_{pk}$ is defined as

$$\hat{S}_{pk} = 3 \Phi^{-1} \left\{ \frac{1}{2} \Phi \left( \frac{USL - \bar{X}}{S} \right) + \frac{1}{2} \Phi \left( \frac{\bar{X} - LSL}{S} \right) \right\},$$

(5)

where $LSL$ and $USL$ are the SLs, as expressed in Section 1.

In what follows, by inspiration of the provided ideas in Besseris (2014) and Aslam et al. (2019), in order to estimate the yield index $S_{pk}$, we define two new robust estimators of $S_{pk}$, which are useful in the presence of outliers.

**Definition 3.** Let $M$ and IQR be the sample median and the sample IQR, respectively. Then, the IQR-based estimator (IE) of $S_{pk}$ is introduced as

$$\hat{S}_{pk}^l = 3 \Phi^{-1} \left\{ \frac{1}{2} \Phi \left( \frac{USL - M}{IQR/3} \right) + \frac{1}{2} \Phi \left( \frac{M - LSL}{IQR/3} \right) \right\},$$

(6)

where the superscript "l" denotes that the IQR of the observations is used as a robust estimator of $3\sigma$.

**Definition 4.** Let $M$ and $1.4826 \times MAD$ be the sample median and the sample standardized MAD, respectively. Then, an MAD-based estimator (ME) of $S_{pk}$, which is used as the robust estimator of $S_{pk}$, is introduced in the following:

$$\hat{S}_{pk}^s = 3 \Phi^{-1} \left\{ \frac{1}{2} \Phi \left( \frac{USL - M}{1.4826 \times MAD} \right) + \frac{1}{2} \Phi \left( \frac{M - LSL}{1.4826 \times MAD} \right) \right\},$$

(7)

where the superscript "s" denotes that the standardized MAD of the observations is used as a more robust estimator of $\sigma$.

It is obvious that the variance of $M$ can be computed by $\text{Var}(M) = \frac{\pi^2}{2n}$ at normal distributions, in which the number $\pi$ ($\pi \approx 3.14159$) is a mathematical constant that is the ratio of a circle’s circumference to its diameter (see more details about the asymptotic distribution of the sample median in Ferguson, 1996).

By inspiration of the presented idea in Bellio and Ventura (2005), in order to estimate an approximate $(1 - x)100\%$ confidence interval for the median of the population, one can consider the following interval:

$$[L_1, L_2] = M \pm z_{1-\alpha/2} \sqrt{\frac{\pi (1.4826 \times MAD)^2}{2n}},$$

(8)

where $z_{1-\alpha/2}$ is the $(1 - \alpha/2)$th quantile of the standard normal distribution. It should be noted that the median of a normal distribution is equivalent to its mean. Therefore, several different possible points from the above interval are considered to apply a robust confidence interval for the location parameter $\mu$, for implementing the steps of the MC simulation in Section 5.

### 3. A comparison study between the non-robust and robust estimation methods

In this section, we are going to a comparison between NE, IE, and ME statistics based on the mean square error (MSE) and the mean absolute deviation ($MAD_{mean}$) criterions. In order to investigate the robustness of different estimation methods against outliers, we consider $m$ random samples, each of size $n$, from the normal distribution with various numbers of outliers ($n_p$). The MSE and $MAD_{mean}$ of the non-robust and robust estimators of $S_{pk}$ for various numbers of outliers are presented in Table 1 and Figure 1. It should be mentioned that the MSE and $MAD_{mean}$ by using $m$ replications, are calculated as

$$MSE = \frac{1}{m} \sum_{i=1}^{m} (\theta - \hat{\theta}_i)^2,$$

(9)

and

$$MAD_{mean} = \frac{1}{m} \sum_{i=1}^{m} |\theta - \hat{\theta}_i|,$$

(10)

where $\hat{\theta}_i$ is the estimator of $\theta$ for $i = 1, \ldots, m$. In order to compute the presented $MSE$ and $MAD_{mean}$ in Table 1 and Figure 1, we perform Algorithm 1 to generate the sample data sets based on considering $m = 1000$, $LSL = 0.0$, $USL = 10.0$, $\mu = 5$, $\sigma = 4$, $\delta = 20$, and $\gamma = 3$ for different sample sizes, $n = 24(44)156$, with various numbers of outliers ($n_p = 0, 1, 2, 3, \text{and } 4$). Note that, by inspiration of Jabbari Nooghabi (2020), we consider that the outliers are occurred from the same distribution but with different parameters in this simulation method.

**Algorithm 1** Simulation method for calculating $MSE$ and $MAD_{mean}$ based on generating $m$ samples each of size $n$ with $n_p$ outliers

**Require:**

1. $n \geq 1$, $n_p \geq 0$, $m \geq 1$, $\sigma, \gamma > 0$, $\mu, \delta, LSL, USL \in \mathbb{R}$.  
2. Probability density for the random variable $X$.  
3. Probability density for the random outlier.
Table 1. Results of the $\text{MSE}$ and $\text{MAD}_{\text{mean}}$ of the PCI $S_{pk}$ for different estimators (NE, IE, and ME) with various numbers of outliers based on the preset SLs $[0.0, 10.0]$.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Sample size</th>
<th>Number of outliers</th>
<th>Non-robust method</th>
<th>Robust method</th>
<th>Robust method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Natural estimator (NE)</td>
<td>IQR-based estimator (IE)</td>
<td>MAD-based estimator (ME)</td>
</tr>
<tr>
<td>$(\mu, \sigma) = (5, 4)$</td>
<td>24</td>
<td>0</td>
<td>0.004 (0.50)</td>
<td>0.321 (0.510)</td>
<td>0.012 (0.082)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.019 (0.126)</td>
<td>0.277 (0.471)</td>
<td>0.011 (0.081)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.034 (0.180)</td>
<td>0.236 (0.427)</td>
<td>0.010 (0.079)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.047 (0.214)</td>
<td>0.159 (0.346)</td>
<td>0.010 (0.084)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.057 (0.238)</td>
<td>0.103 (0.267)</td>
<td>0.014 (0.100)</td>
</tr>
<tr>
<td>Result of simulation based on a normal distribution</td>
<td>68</td>
<td>0</td>
<td>0.001 (0.028)</td>
<td>0.279 (0.510)</td>
<td>0.004 (0.048)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.001 (0.064)</td>
<td>0.263 (0.495)</td>
<td>0.004 (0.047)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.012 (0.101)</td>
<td>0.243 (0.476)</td>
<td>0.003 (0.045)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.018 (0.131)</td>
<td>0.220 (0.450)</td>
<td>0.003 (0.048)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.025 (0.156)</td>
<td>0.206 (0.435)</td>
<td>0.004 (0.050)</td>
</tr>
<tr>
<td></td>
<td>112</td>
<td>0</td>
<td>0.001 (0.022)</td>
<td>0.273 (0.512)</td>
<td>0.002 (0.037)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.003 (0.044)</td>
<td>0.260 (0.499)</td>
<td>0.002 (0.038)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.006 (0.072)</td>
<td>0.243 (0.482)</td>
<td>0.002 (0.036)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.010 (0.098)</td>
<td>0.240 (0.480)</td>
<td>0.002 (0.037)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.014 (0.117)</td>
<td>0.230 (0.469)</td>
<td>0.002 (0.037)</td>
</tr>
<tr>
<td></td>
<td>156</td>
<td>0</td>
<td>0.001 (0.019)</td>
<td>0.264 (0.506)</td>
<td>0.002 (0.031)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1</td>
<td>0.002 (0.034)</td>
<td>0.259 (0.501)</td>
<td>0.002 (0.031)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2</td>
<td>0.004 (0.056)</td>
<td>0.252 (0.495)</td>
<td>0.002 (0.031)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3</td>
<td>0.007 (0.077)</td>
<td>0.244 (0.486)</td>
<td>0.001 (0.031)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4</td>
<td>0.010 (0.094)</td>
<td>0.238 (0.481)</td>
<td>0.002 (0.031)</td>
</tr>
</tbody>
</table>

Figure 1. The $\text{MSE}$ (left graphs) and the $\text{MAD}_{\text{mean}}$ (right graphs) of the PCI $S_{pk}$ for different estimators (NE, IE, and ME) with various numbers of outliers ($n_p = 0, 1, 2, 3, \text{ and } 4$).

Ensure: $\text{MSE}$ and $\text{MAD}_{\text{mean}}$ of three estimators $\hat{S}_{pk}, \hat{S}_{pk}^f$, and $\hat{S}_{pk}^r$ (NE, IE, and ME).

for $i = 1$ to $m$

Generate independently $X_{1,i}, \ldots, X_{n-n_p,i} \sim N(\mu, \sigma^2)$.

Generate independently $X_{n-n_p+1,i}, \ldots, X_{n,i} \sim N(\mu + \delta, \gamma \sigma^2)$.

Combine two samples $(X_{1,i}, \ldots, X_{n-n_p,i})$ and $(X_{n-n_p+1,i}, \ldots, X_{n,i})$ to achieve $\{X_{1,i}, \ldots, X_{n-n_p,i}, X_{n-n_p+1,i}, \ldots, X_{n,i}\}$.

Compute $\hat{S}_{pk,i}$ based on the sample data set $\{X_{1,i}, \ldots, X_{n,i}\}$ by Eq. (5).

Compute $\hat{S}_{pk,i}^f$ based on the sample data set $\{X_{1,i}, \ldots, X_{n,i}\}$ by Eq. (6).

Compute $\hat{S}_{pk,i}^r$ based on the sample data set $\{X_{1,i}, \ldots, X_{n,i}\}$ by Eq. (7).

end for

Calculate $S_{pk}$ from Eq. (1).

1. Calculate $\text{MSE}$ of three estimators $\hat{S}_{pk}, \hat{S}_{pk}^f$, and $\hat{S}_{pk}^r$ by Eq. (9).
2. Calculate $\text{MAD}_{\text{mean}}$ of three estimators $\hat{S}_{pk}, \hat{S}_{pk}^f$, and $\hat{S}_{pk}^r$ by Eq. (10).
return \( \text{MSE} \) and \( \text{MAD}_{\text{mean}} \) of three estimators \( \hat{S}_{pk}, \hat{S}_{pk}^r, \) and \( \hat{S}_{pk}^r \) (NE, IE, and ME).

For instance, in the last column of Table 1, for \( n = 24 \) with one outlier (\( n_p = 1 \)), we generate \( m = 1000 \) samples, each of size \( n - n_p = 24 - 1 = 23 \) from the normal distribution \( \mathcal{N}(\mu = 5, \sigma^2 = 4^2) \) \((X_{1,i}, \ldots, X_{23,i}) \sim \mathcal{N}(5, 4^2)\) for each \( i = 1, \ldots, 1000\), and also for having one outlier in the sample data set, we generate 1000 samples, each of size one from the normal distribution with different parameters \((X_{24,i} \sim \mathcal{N}(\mu + 20, 3\sigma^2)\) for each \( i = 1, \ldots, 1000\). Consequently, by performing Algorithm 1 on the basis of using the ME of \( S_{pk}^r \), for each \( i = 1, \ldots, 1000 \), the \( \text{MSE} \) and \( \text{MAD}_{\text{mean}} \) of \( \hat{S}_{pk,i}^r \) are computed by the following formulas in this simulation study:

\[
\text{MSE} = \frac{1}{1000} \sum_{i=1}^{1000} (S_{pk,i} - \hat{S}_{pk,i}^r)^2 = 0.011,
\]

and

\[
\text{MAD}_{\text{mean}} = \frac{1}{1000} \sum_{i=1}^{1000} |S_{pk,i} - \hat{S}_{pk,i}^r| = 0.081,
\]

where \( S_{pk} \) is calculated by

\[
S_{pk} = \frac{1}{3} \Phi^{-1}\left( \frac{1}{2} \Phi \left( \frac{10 - 5}{4} \right) + \frac{1}{2} \Phi \left( \frac{5 - 0}{4} \right) \right) = 0.417.
\]

The results of Table 1 and Figure 1 showed that the sample size has a significant impact on both \( \text{MSE} \) and \( \text{MAD}_{\text{mean}} \) for the non-robust and robust estimation methods (NE, IE, and ME). By comparing the results of these methods, one can observe that the best result is on the basis of using the ME of \( S_{pk}^r \) \((\hat{S}_{pk}^r)\), since different numbers of outliers have the least impact on both \( \text{MSE} \) and \( \text{MAD}_{\text{mean}} \) for this estimator. Hence, with regard to the values of both \( \text{MSE} \) and \( \text{MAD}_{\text{mean}} \) in this simulation study, one can conclude that the proposed ME of \( S_{pk} \) is a more robust estimator to the outliers.

Exclusively, the robust yield test on the basis of using the proposed estimator \( \hat{S}_{pk}^r \) is presented in the next section. The proposed test is useful to make a reliable decision on evaluating the performance of the normal process, which can be affected by outliers.

4. Decision-making components in testing the production yield

Throughout this study, it is supposed that the quality characteristic is approximately normally distributed and the process is in a state of statistical control. To determine whether the production process is capable or not, one can consider the following hypotheses test:

\[
\begin{align*}
H_0 & : \text{Yield} \leq c_0 \quad \text{(process is incapable)}, \\
H_1 & : \text{Yield} > c_0 \quad \text{(process is capable)},
\end{align*}
\]

in which the designed constant \( c_0 \) is the standard minimal criterion for the process yield. It must be mentioned that the designed constant \( c_0 \) is a stringent requirement for the possible mean shift or the variation change which is determined by the producer in the factory/company. In many cases, a minimal criterion 99.73% \((c_0 = 0.9973)\) for evaluating the process is suggested. According to the existence a one-to-one relationship between the production yield and the PCI \( S_{pk} \) (see Eq. (2)), testing the above hypotheses is equivalent to testing

\[
\begin{align*}
H_0 & : S_{pk} \leq s_0, \\
H_1 & : S_{pk} > s_0,
\end{align*}
\]

where \( s_0 = \frac{1}{3} \Phi^{-1} \left( \frac{1}{2} \Phi \left( 10 - 5 \right) + \frac{1}{2} \Phi \left( 5 - 0 \right) \right) \) is the standard minimal criterion for the PCI \( S_{pk} \), which is determined based on the designed constant \( c_0 \).

For making a decision, one can use the components of the decision-making—such as the \( p \) value, the critical value, the probability of type II error, and the power function of the robust yield test—to assess the production yield based on the PCI \( S_{pk} \). Herein, we intend to consider the following test function:

\[
\phi(x_1, x_2, \ldots, x_n) = \begin{cases} 
1, & \hat{S}_{pk}^r > s, \\
0, & \text{otherwise},
\end{cases}
\]

where \( s \) is the critical value in testing hypotheses (Iranmanesh, Parchami, and Sadeghpour Gildeh 2022). Suppose the probability that an incapable process is mistakenly considered capable, is \( \alpha \) (the significant level of the proposed robust yield test). Then, \( \phi(x_1, x_2, \ldots, x_n) \) rejects the null hypothesis \( H_0 \) \((S_{pk} \leq s_0)\) if \( \hat{S}_{pk}^r > s \) (i.e., the process is capable). Also,

\[
\alpha = P(\hat{S}_{pk}^r > s | S_{pk} = s_0),
\]

is the probability of type I error. Hence, we can write

\[
1 - \alpha = P(\hat{S}_{pk}^r \leq s | S_{pk} = s_0).
\]

Therefore, the critical value of this robust yield test is the \((1 - \alpha)\) th quantile of \( \hat{S}_{pk}^r \) distribution such that
S_{pk} = s_0$. On the other hand, the $p$ value of this robust yield test is given by

$$p\text{-value} = P\left(\tilde{S}'_{pk} > \tilde{s}_{pk} | S_{pk} = s_0\right) = E\left[I\left(\tilde{S}'_{pk} > \tilde{s}_{pk} | S_{pk} = s_0\right)\right],$$

where $\tilde{s}_{pk}$ is the observed ME of $S_{pk}$ on the basis of observations $x_1, \ldots, x_n$, which is computed by Eq. (7), while the indicator function of an event $A$ is indicated by $I(A)$. Also, the probability of type II error can be calculated as

$$\beta(s_{pk}) = P\left(\tilde{S}'_{pk} \leq s | S_{pk} = s_{pk}\right) = E\left[I\left(\tilde{S}'_{pk} \leq s | S_{pk} = s_{pk}\right)\right],$$

for any arbitrary point $s_{pk} > s_0$. Hence, for every $S_{pk} > 0$

$$\Pi(S_{pk}) = 1 - \beta(S_{pk}) = P\left(\tilde{S}'_{pk} > s | S_{pk}\right) = E\left[I\left(\tilde{S}'_{pk} > s | S_{pk}\right)\right],$$

is the power function of the proposed robust yield test based on the yield index $S_{pk}$.

### 5. Monte Carlo simulation method

In this section, we intend to propose the MC simulation method (MC method) based on the proposed robust estimator $\tilde{S}'_{pk}$ for estimating the decision-making components.

#### 5.1. Methodology

To simulate the components of the decision-making for the statistical testing with null hypothesis $H_0$: $\text{Yield} \leq c_0$ versus alternative hypothesis $H_1$: $\text{Yield} > c_0$, at the considered significance level, $\alpha$, we propose the following procedure as the MC-method:

**Step 1.** Test the null hypothesis $H_0$: $S_{pk} \leq s_0$ versus alternative hypothesis $H_1$: $S_{pk} > s_0$, which is equivalent for testing $H_0$: $\text{Yield} \leq c_0$ versus $H_1$: $\text{Yield} > c_0$, to specify whether a production process is capable or not. Then, based on the existence of a one-to-one relationship between the production yield and the index $S_{pk}$, compute the standard minimal criterion $s_0$ by substituting $c_0$ and $s_0$ to Eq. (2) as

$$s_0 = \frac{1}{3}\Phi^{-1}\left(\frac{c_0 + 1}{2}\right),$$

where $c_0$ is the designed constant for testing the process yield.

**Step 2.** By Eq. (7), calculate the observed value of the robust estimator $\tilde{s}_{pk}$ based on the observations $x_1, \ldots, x_n$.

**Step 3.** Compute the sequence $\{\mu_1, \mu_2, \ldots, \mu_k\}$ to cover several different possible points from the interval $[L_1, L_2]$ by the formula

$$\mu_j = L_1 + \frac{j - 1}{h - 1}(L_2 - L_1), j = 1, 2, \ldots, h,$$

where $L_1$ and $L_2$ are computable by Eq. (8) based on the observations $x_1, x_2, \ldots, x_n$. The positive natural number $h$ specifies the number of the $\mu_j$ that can be selected according to the sensitivity of the applicant. It must be noted that the greater the spread of the observed data, the greater $h$ is recommended in the simulation.

**Step 4.** Follow the below (i)–(vi) parts for $j = 1, \ldots, h$:

(i) calculate the unknown root $\sigma_j$ on the basis of $\mu_j$ from

$$\frac{1}{3}\Phi^{-1}\left(\frac{1}{2}\Phi\left(\frac{USL - \mu_j}{\sigma_j}\right) + \frac{1}{2}\Phi\left(\frac{LRL - \mu_j}{\sigma_j}\right)\right) = s_0,$$

(ii) considering $k = 10^3$, simulate $k$ random samples with size $n$ from $N(\mu_j, \sigma_j^2)$,

(iii) by Eq. (7), estimate $\tilde{s}_{pk,j}^{(r_1)}, \tilde{s}_{pk,j}^{(r_2)}, \ldots, \tilde{s}_{pk,j}^{(r_k)}$ for every simulated sample in Part (i),

(iv) according to Eq. (3), the critical value based on 1000 simulated samples is equivalent to the $(1 - \alpha)$th quantile of $\tilde{S}'_{pk}$ distribution,

$$s_j = \tilde{s}_{pk,j}^{(\lceil \alpha(k - 1) \rceil)},$$

where $\tilde{s}_{pk,j}^{(1)}, \tilde{s}_{pk,j}^{(2)}, \ldots, \tilde{s}_{pk,j}^{(k)}$ are the ordered indices from Part (iii), and $\lceil t \rceil$ is the smallest integer greater than or equal to $t$.

(i) the simulated $p$ value is equal to

$$p\text{-value}_j = \frac{1}{k}\sum_{i=1}^{k} I\left(\tilde{s}_{pk,j}^{(r_i)} > \tilde{s}_{pk} \mid \mu = \mu_j, \sigma = \sigma_j\right),$$

(ii) where the estimated indices are indicated by $\tilde{s}_{pk,j}^{(r_1)}, \ldots, \tilde{s}_{pk,j}^{(r_k)}$ and $s_j$ is the obtainable root of the equation $s_{pk} = s_0$ from Part (i),

(i) the simulated $\beta_j$ for every point $s_{pk} > s_0$, is

$$\beta_j(s_{pk}) = \frac{1}{k}\sum_{i=1}^{k} I\left(\tilde{s}_{pk,j}^{(r_i)} \leq s_j \mid \mu = \mu_j, \sigma = \sigma_j\right),$$

where $c_0$ is the designed constant for testing the process yield.
where \( \sigma^*_j \) is the obtainable root from the following equation
\[
\frac{1}{3} \Phi^{-1}\left\{ \frac{1}{2} \Phi\left( \frac{USL - \mu_j}{\sigma^*_j} \right) + \frac{1}{2} \Phi\left( \frac{\mu_j - LSL}{\sigma^*_j} \right) \right\} = s_{pk}^*.
\]  
(25)

Likewise, the estimated indices based on \( \mu_j \) and \( \sigma^*_j \) are indicated by \( s_{pk[j]}^{r[1]}, \ldots, s_{pk[j]}^{r[k]} \).

**Step 5.** The MC critical value of this proposed robust yield test is equivalent to
\[
s_{MC} = \frac{1}{h} \sum_{j=1}^{h} s_j.
\]  
(26)

**Step 6.** The null hypotheses in Eqs. (11) and (12) are rejected at the significance level of \( \alpha \), if \( s_{pk}^* > s_{MC} \) (i.e., the process is capable); otherwise, the process is incapable.

**Step 7.** The MC \( p \)-value in the proposed robust yield test is equivalent to
\[
p-value_{MC} = \frac{1}{h} \sum_{j=1}^{h} p-value_j.
\]  
(27)

**Step 8.** The MC probability of type II error for any point \( s_{pk}^* > s_0 \) can be simulated in the proposed robust yield test by the total average of \( h \) calculated probability of type II errors at the fixed point \( s_{pk}^* \) in repetitions of Part (vi), that is,
\[
\beta_{MC}(s_{pk}^*) = \frac{1}{h} \sum_{j=1}^{h} \beta_j(s_{pk}^*).
\]  
(28)

**Remark 1** Note that the power function of the robust yield test in the proposed MC-method for every \( S_{pk} > 0 \) is equal to
\[
\Pi_{MC}(S_{pk}) = 1 - \beta_{MC}(S_{pk}).
\]  
(29)

### 5.2. Generalization of the robust yield test based on some non-normal processes

Generally, the yield index \( S_{pk} \) is applied based on the normal distribution of process output. Also, it has a one-to-one relation with the production yield. Typically, the first idea for non-normality assumptions is using the surrogate PCIs based on Clements's percentile method (Clements, 1989) for non-normal production processes. But based on the lack of the existence of a one-to-one relationship between the proposed Clements's PCIs and the production yield, we prefer to transform non-normal data by Box–Cox method (Box and Cox, 1964) which can be useful to normalize some non-normal variables. Given a random variable \( X \) from any distribution with only positive values, we consider the following family of the transformation:

\[
Y = \begin{cases} 
\frac{X^\lambda - 1}{\lambda}, & \lambda \neq 0, \\
\log(X), & \lambda = 0,
\end{cases}
\]  
(30)

where \( \lambda \in \mathbb{R} \) is the Box–Cox transformation parameter. Box and Cox (1964) presented the maximum likelihood and Bayesian methods to estimate the parameter \( \lambda \).

**Remark 2** Note that the methodology of the MC-method is proposed for the normal distribution of the process output. Under the non-normality assumption, if the Box–Cox transformation method is able to transform non-normal data into normal data, then by considering the following points one can generalize the MC-method:

1. The generalization idea is used for the family of distributions with only positive values such as the log-normal, weibull, gamma, and the generalized exponential distribution.
2. Box–Cox transformation method is applied to transform the original data \((x_1, \ldots, x_n)\) into normal data. Hence, one can use each type of goodness-of-fit tests (Shapiro–Wilk test, Lilliefors test, and Robust Jarque–Bera test of normality) to confirm the normality assumption of the transformed observations \((y_1, \ldots, y_n)\).  
3. After confirming that the normal distribution model is suitable to fit the transformed data, the observed value of robust estimator \( s_{pk}^* \) can be calculated based on the transformed observations \((y_1, \ldots, y_n)\) for implementing the steps of the simulation in the MC-method.

The following section presents the obtained results corresponding to the application of the robust yield test using a real dataset.

### 6. Illustrative example and numerical results

#### 6.1. Numerical results

Capacitors are invaluable parts of electronic devices—such as laptops, biomedical devices, and satellites—that have duties to retain the voltage at a certain level. Capacitors are used for reducing the voltage pulsation. An aluminum foil is an important part that affects the quality of capacitors. The voltage is the most
Furthermore, on the basis of the box plot and the histogram, observations are contaminated with one outlier (Figure 4).

Meanwhile, the value of the observed median is 522.55, and the observed standardized MAD is equal to 2.82. Hence, the robust estimator of $S_{pk}$ according to Eq. (7) is

$$
\hat{z}^r_{pk} = \frac{1}{3} \Phi^{-1} \left\{ \frac{1}{2} \Phi \left( \frac{USL - 522.55}{2.82} \right) + \frac{1}{2} \Phi \left( \frac{522.55 - LSL}{2.82} \right) \right\} = 0.957.
$$

Therefore, $0.957 < s_{MC}$ is the MC critical region of the test based on the PCI $S_{pk}$ at the significance level of 0.01, where the critical value $s_{MC}$ should be simulated based on the MC-method. It must be noted that this proposed method, which is presented in Section 5, is performed based on the observed robust estimator $\hat{z}^r_{pk}$ where the mean is changed over the following sequence according to Eq. (20):

$$
$$

The unknown root $\sigma_j$ is computed in Table 2 for all $h = 8$ considered possible cases from Eq. (21). Therefore, for each case, 1000 independent random samples are simulated with size 50 from $N(\mu_j, \sigma_j^2)$. In every simulated sample, we estimate the index $S_{pk}$ based on observations $x_1, x_2, \ldots, x_{50}$ according to Eq. (7). After ordering 1000 estimated indices, the 990th index is selected as the critical value, and the results are recorded in Table 2 for all eight considered cases. For instance, in the sixth row of Table 2, the following results are obtained:

- $\mu_5 = 522.694$ is the sixth considered value for $\mu$ in the simulation using Step 3 from the proposed MC-method,
- $\sigma_6 = 2.626$ is the computed value of $\sigma$ for $j = 6$ using Part (i),
- $s_6 = 1.519$ is the simulated critical value using Part (iv),
- $p$ value $6 = 0.657$ is the simulated $p$ value using Part (v), and
- $\beta_6(1.98) = 0.026$ is the simulated $\beta$ at the fixed point 1.98 using Part (vi) of Step 4 from the MC-method.

Monte Carlo critical values of the considered yield test are determined in Table 2 for eight possible values of the process mean to make a decision on the robust yield test in this study. Moreover, the last row
of this table contains the MC critical value, the MC $p$ value, and the MC probability of type II at the fixed point 1.98, respectively. Consequently, in evaluating based on the robust estimator $\hat{S}_{pk}$, the average of eight obtained critical values is equivalent to $s_{MC} = 1.512$, which is considered the MC critical value for testing the quality of the production process. Hence, with regard to the preset SLs in this illustrative example, the null hypothesis $H_0 : S_{pk} < s_0$ is not rejected at the significance level of $\alpha = 0.01$, because $\hat{S}_{pk} = 0.957 < s_{MC}$, therefore, one can conclude that this process cannot meet the capability requirement at the significance level of 0.01.

### 6.2. Simulation results

For the purpose of investigating whether outliers can affect decisions in a robust yield test, we present the numerical results of the simulation method by using Algorithm 1 for generating $m$ samples each of size $n$ with $n_p$ outliers. In order to compare the original data (VAFs observations) and the simulated data in testing the production yield, we intend to use the mean and standard deviation of the original observed data (VAFs data) for estimating the mean and standard deviation parameters of the normal distribution, respectively. These two values are obtained $\bar{x} = \sum_{i=1}^{50} x_i/50 = 522.172$ and $s_{n-1} = \sqrt{\sum_{i=1}^{50} (x_i - \bar{x})^2/(50 - 1)} = 2.974$ from VAFs data, respectively. Firstly, allow us to use Algorithm 1 for generating the sample data sets based on considering $m = 1$, $LSL = 510$, $USL = 530$, $\mu = 522.172$, $\sigma = 2.974$, $\delta = 16$, and $\gamma = 3$ for the sample size $n = 50$, with various numbers of outliers ($n_p = 0$, 1, and 2). Under the desired quality condition with $s_0 = 0.9973$ ($s_0 = 1.00$), and $\alpha = 0.01$, the power function of the proposed test $\Pi_{MC}(S_{pk})$ on the basis of the following considered samples is presented in Table 3 for the considered points $S_{pk} = 1.25(0.01)1.86$:

a. The original data (VAFs data, in which the value of the outlier is 514.700).
b. The simulated sample data without outliers,
c. The simulated sample data with the presence of one outlier (the value of the outlier is 537.341).
The simulated sample data with the presence of two outliers (the values of outliers are 536.284 and 538.055).

It should be mentioned that the values of outliers in the above parts (a)–(d) are detected according to the threshold in Eq. (4).

The results of Table 3 showed that the presence of outliers in the VAFs data and the simulated data do not have a significant impact on changing the power function of the proposed test \( \Pi_{MC} (S_{pk}) \) on the basis of the considered samples in parts (a)–(d). For example, in the first row of Table 3, for the considered point \( S_{pk} = 1.25 \), based on the considered samples in parts (a)–(d), the values of the power function of these four quality tests are approximately equivalent (i.e., because the values of the power function of the proposed test \( \Pi_{MC} (S_{pk}) \) by changing in the number of outliers close approximately together for each considered point \( S_{pk} \), one can conclude that our proposed method for testing the performance of the production process in the illustrative example (VAFs observations in subsection 6.1) is a robust method).

Furthermore, in order to show that the presence of outliers often does not have a huge impact on making the decision in the proposed robust yield test, we use Algorithm 1 to generate the sample data sets based on considering \( m = 200, LSL = 510, USL = 530, \mu = 522.172, \sigma^2 = 2.974^2, \delta = 16, \gamma = 3 \) for different sample sizes, \( n = 16, 20, 24, 30, 35, 50, 100, \) and 150, with various numbers of outliers (\( n_p = 0, 1, 2 \)).

For this purpose, we should consider \( \phi_i (x_1, x_2, ..., x_n) \) as the test function that rejects the null hypothesis \( H_0 : S_{pk} \leq 1.00 \) if \( S_{pk,i} > s_{MC,i} \) where \( s_{MC,i} \) is the simulated MC critical value in testing hypotheses (Iranmanesh, Parchami, and Sadeghpour Gildeh 2022), for \( i = 1, 2, ..., 200 \). Therefore, the calculated percentage of rejecting the null hypothesis \( H_0 : S_{pk} \leq 1.00 \) on the basis of the sample data set which are simulated from the considered normal distribution \( N(\mu = 522.172, \sigma^2 = 2.974^2) \) with the presence of various numbers of outliers (0, 1, and 2), are presented in Table 4 under the desired quality condition with \( c_0 = 0.9973 \) (\( c_0 = 1.00 \)), and \( \alpha = 0.01 \).

Both Tables 3 and 4 are presented as the confirmations of the correctness and robustness of the proposed yield test with the difference that Table 3 is merely the presentation of a comparison between the VAFs observations and the considered samples in parts (b)–(d), and Table 4 are provided in a general.

### Table 3. Results of the simulated MC power function of the proposed test \( \Pi_{MC} (S_{pk}) \) on the basis of four considered samples in parts (a)–(d) (A comparison between the VAFs data and the simulated samples with the presence of zero, one, and two outliers), under the desired quality condition with \( LSL = 510, USL = 530, c_0 = 0.9973 \) (\( s_0 = 1.00 \)), and \( \alpha = 0.01 \).

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<th>( S_{pk} )</th>
<th>(a)</th>
<th>(b)</th>
<th>(c)</th>
<th>(d)</th>
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The results of Table 3 showed that the presence of outliers in the VAFs data and the simulated data do not have a significant impact on changing the power function of the proposed test \( \Pi_{MC} (S_{pk}) \) on the basis of the considered samples in parts (a)–(d). For example, in the first row of Table 3, for the considered point \( S_{pk} = 1.25 \), based on the considered samples in parts (a)–(d), the values of the power function of these four quality tests are approximately equivalent (i.e., because the values of the power function of the proposed test \( \Pi_{MC} (S_{pk}) \) by changing in the number of outliers close approximately together for each considered point \( S_{pk} \), one can conclude that our proposed method for testing the performance of the production process in the illustrative example (VAFs observations in subsection 6.1) is a robust method).
confirmation. Herein, in order to show that the change of our decision is not big based on changing in the number of outliers in the simulated data, the values of the percentage of rejecting the null hypothesis \( H_0 \) are presented in Table 4, and because the values of percentages by changing in the number of outliers close approximately together for each \( n \), one can conclude that our proposed method for testing the performance of a production process is the robust method. For example, in the third row of Table 4, for the considered sample size \( n = 16 \) with the presence of one outlier \( (n_p = 2) \), the value of the percentage of rejecting the null hypothesis \( H_0 : S_{pk} \leq 1.00 \) based on the simulated data is 0.5% (this value is very small, i.e., one robust estimator from 200 robust estimators \( S_{pk,i} \) is greater than the simulated MC critical value \( S_{MC,i} \), for \( i = 1, 2, \ldots, 200 \), that is one test function from 200 test functions \( \phi_i(x_1, x_2, \ldots, x_n) \) rejects the null hypothesis \( H_0 : S_{pk} \leq 1.00 \), and one can conclude that the null hypothesis \( H_0 : S_{pk} < s_0 \) is not rejected at the significance level of \( \alpha = 0.01 \). Generally, in order to show that the changes of making the decision are not huge, we added the average of percentages of rejecting the null hypothesis \( H_0 : S_{pk} \leq 1.00 \) in the last row of Table 4 (i.e., by changing in the number of outliers for the simulated data, the values of 0.25%, 0.19%, and 0.13% close approximately together for making a reliable decision). Hence, based on the results of Table 4, one can conclude that the null hypothesis \( H_0 : S_{pk} < s_0 \) is not rejected at the significance level of \( \alpha = 0.01 \), and also, this conclusion corresponds to the conclusion in subsection 6.1 that the production process based on the original data (VAFs observations) cannot meet the capability requirement at the significance level of 0.01. Therefore, based on these results, we confirm the correctness and robustness of our proposed yield test.

### 7. Comparison study between the proposed MC-method and various methods

Traditional PCIs, such as, \( C_p \), \( C_{pk} \) and \( C_{pm} = \frac{USL - LSL}{6\sqrt{\sigma^2 + (\mu - T)^2}} \) have many applications in the manufacturing industry, where \( LSL \), \( USL \), \( \mu \), and \( \sigma \) are expressed in Section 1, and \( T \) is the target value. In this section, we are going to test the quality of inside diameters of piston rings with different PCIs \( C_p \), \( C_{pk} \), \( C_{pm} \), and \( S_{pk} \) based on various presented methods at different significance levels. It must be noted that the piston rings data (with the detected values of outliers 73.967 and 74.030) are available by “qcc” package in R software (Scrucca 2004). Shapiro–Wilk test shows that the piston rings data follow normal distribution.
(\(p\) value = 0.7861). Based on the standard minimal criterion \(c\) for the considered PCIs \(C_p\), such that \(n \in \{p, pk, pm\}\), we consider the following hypotheses

\[
\begin{align*}
H_0 & : C_p \leq c, \\
H_1 & : C_p > c,
\end{align*}
\]

and the hypotheses (Iranmanesh, Parchami, and Sadeghpour Gildeh 2022) to test the quality of the production process in this comparison study. It must be clarified that the decision-making components for the proposed MC-method are compared with various presented methods (Iranmanesh, Parchami, and Sadeghpour Gildeh 2022; Pearn and Kotz 2006; Pearn and Chuang 2004) in Table 5. Therefore, four following non-robust and robust quality tests are considered based on the value of the standard minimal criterion \(1.00\) in Table 5 at different significance levels for inside diameters of piston rings:

1. non-robust quality test based on \(C_p\), for the considered SLs [73.96, 74.03],

2. non-robust quality test based on \(C_{pm}\), for the considered SLs [73.96, 74.03] and target value \(T = 73.999\),

3. non-robust quality test based on \(C_{pk}\), for the considered SLs [73.96, 74.03], and

4. robust quality test based on \(S_{pk}\), for the considered SLs [73.96, 74.03].

For each case, the critical value, the \(p\) value, and the probability of type II error based on the considered NEs \(\tilde{C}_p = \frac{USL - LSL}{6\sigma}, \tilde{C}_{pm} = \frac{USL - LSL}{6\sqrt{S_x^2 + \frac{(X - T)^2}{n}}}, \tilde{C}_{pk} = \min \left\{ \frac{USL - X}{3\sigma}, \frac{LSL - X}{3\sigma} \right\}\), and the proposed robust estimator \(\tilde{S}_{pk}^*\) were computed and shown in Table 5 at significance levels of 0.010, 0.025, 0.05, and 0.1. It must be mentioned that the statistical critical value based on the NE \(\tilde{C}_p\) was calculated by \(c \sqrt{\frac{n - 1}{\hat{\sigma}^2}}\), where \(c\) is the standard minimal criterion and \(\chi_{m-1, x}^{2}\) is the lower \(x\)-quantile of the chi-square distribution with \(n - 1\) degrees of freedom (Pearn and Kotz 2006). Moreover,
the critical values based on the NEs \( \hat{C}_{pm} \) and \( \hat{C}_{pk} \) were simulated in Iranmanesh, Parchami, and Sadeghpour Gildeh (2022) and Pearn and Chuang (2004) on the basis of the Monte Carlo simulation methods. By comparing the results of Table 5, one can observe that both critical value and \( p \) value increase in the proposed MC-method. Therefore, the more reliable result is on the basis of using the proposed MC-method, since this procedure is based on the robust quality test and outliers cannot affect on it.

8. Conclusions and future works

The evaluation of the production process performance was investigated in this article by using the yield index \( S_{pk} \). Testing the performance of a production process is an effective technique for making a decision on the process yield/capability. It was widely discussed that the presence of outliers might have a deleterious effect on statistical analyses and decisions. In this regard, a robust estimator of \( S_{pk} \) based on the MAD-based method was introduced to test the production yield. A comparison study was shown that the outliers have the least impact on both mean square error and mean absolute deviation for the proposed robust estimator of \( S_{pk} \). Moreover, an MC simulation method was applied to estimate the components of the decision-making for testing the process yield based on the index \( S_{pk} \) by normal data. Meanwhile, this article discussed how well the MC-method can be used for some non-normal data. Numerical results of the simulation and real data analyses were presented to explain the proposed method. As a future study, one can develop the rule of the proposed robust yield test to assess the performance of processes with multiple characteristics.

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