

Improved Wald Transformation p -Chart For Nonconforming Fraction

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This study proposes a new improved transformation p -chart for nonconforming fraction of a production process, called improved Wald transformation p -chart. Via a simulation study, the efficiency of the proposed control chart was compared with the traditional p -chart, the improved square root transformation p -chart, and the Wilson p -chart. The simulation was conducted using the Monte Carlo technique for 180 situations and 10,000 times for each situation. The studied situations were as follows: the nonconforming fraction was set to be 0.01, 0.02, 0.05, 0.07, and 0.09; the shift of the nonconforming fraction was set to be 1.1, 1.3, 1.5, 2.0, 3.0, and 4.0; and the sample size (n) was set to be 30, 50, 100, 300, 500, and 1000. The efficiency measures were out-of-control average run length and standard deviation of the run length. The results showed that the proposed chart was the most efficient among the four tested charts for a large sample size. In addition, the proposed chart tended to perform with the best efficiency for large sample sizes, $n \geq 500$, and small nonconforming fraction below 0.1. It performed well with all the tested shifts of nonconforming fraction. However, the sensitivity to detect out-of-control items in the production process seemed to be same among the tested charts for smaller sample size, $n < 500$.

Keywords: nonconforming fraction; p -chart; run length; transformation

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1. Introduction

The success of a production process depends on factors and various steps that were specified from the beginning of the process. In addition, a good production process plan will help reduce costs and production time. It also reduces various risks in production and increases the ability to respond to customer needs more quickly. A good production process will help business to be successful and grow sustainably. Nowadays, manufacturing competition is quite high. Product quality plays an important role in consumer purchasing decision, i.e., product quality must meet consumer needs [1]. Many factors affect product quality, factors such as employees, machines, raw materials, etc. If these factors are proper and do not change with time, the product will meet the required quality [2-5]. Therefore, it is necessary to control the manufacturing process so that it

meets the desired quality at low cost. Control chart is the most popular statistical process control (SPC) instrument for detection of abnormalities in production process [2-4]. If the process operator can quickly detect and solve an out-of-control process problem, the loss can be minimized. A widely used attribute control chart for detecting the fraction of nonconforming items in a production process is a nonconforming fraction control chart, usually called a p -chart. A problem with this chart is its slowness in detecting process changes [6-13]. Many studies have concluded that the traditional p -chart did not perform well. There have been several ways to improve p -chart. After it is improved, it should be more sensitive to detect process abnormalities when the nonconforming fraction in the process slightly changes from the target. In the past, p -chart was improved based on the idea of several kinds of transformations. Chen

[14] improved p -chart with simple adjustments to the control limits of the p -chart. He compared the efficiency of the improved p -chart, arcsine p -chart and Q chart and found that the improved p -chart and Q chart were efficient for large nonconforming fraction. In the real world, a small nonconforming fraction often occurs in the production process, so p -chart is not the appropriate tool [15, 16]. An improved square root transformation p -chart, ISRT p -chart, was proposed by Tsai et al. [15]. The efficiencies of four charts—exact p , modified p , regression-based p , and ISRT p —were compared via a numerical study. The ISRT p -chart and the exact p -chart performed with the same efficiency, adequate for a low level of nonconforming fraction. Later in 2014, Sukparungsee [12] found that ISRT p -chart performed well for the shift in nonconforming fraction of over 0.5, the nonconforming fraction level (p_0) of 0.05 and 0.1, and the sample size (n) of 50 and 70. In 2012, Anna and Caten [17] proposed a new control chart, a beta chart, for monitoring nonconforming fraction when data were taken from binomially distributed population. Their proposed control limits were derived based on the beta distribution which is an approximation to the binomial distribution. This distribution is more appropriate for values of the random variable between 0 and 1. The efficiency comparison was studied via a simulation of situations consisting of nonconforming fraction (p_0) of 0.001, 0.01, and 0.10; sample size (n) of 50, 200, 300, and 1500; and the shift of nonconforming fraction (δ) in production process of 0.001, 0.01, and 0.02. The results show that the beta chart was more sensitive for process monitoring in terms of in-control (ARL_0) and out-of-control (ARL_1) average run lengths. In addition, this proposed chart is better than the classical chart [18] for monitoring nonconforming fractions. Furthermore, Rungruang [19] compared the efficiencies of three charts—Q chart, moving average p -chart, and beta chart—in monitoring nonconforming fractions. For an out-of-control process, the beta control chart was the most efficient for a small nonconforming fraction and a small shift in nonconforming fraction. However, the moving average p -chart was more suited for a large nonconforming fraction and a large shift in nonconforming fraction, regardless of the sample size. Two years later, Rod-o et al. [13] used the concept of adjusted Wald confidence interval estimation [20] to develop control limits of p_{AC} chart for monitoring nonconforming fraction. They compared its efficiency with those of three charts: beta chart, moving average p -chart, and p -chart. The beta chart was the most effective for almost all levels of shift in nonconforming fraction and sample sizes when the nonconforming fraction was small. However, the moving average p -chart was more effective for a

large nonconforming fraction. Furthermore, the proposed p_{AC} chart provided a good performance for almost all nonconforming fractions and sample sizes when the shift in nonconforming fractions increased. In addition, Tsai et al. [15] proposed the ISRT p -chart and compared it with several other kinds of charts. Small sample sizes were required to obtain positive lower control limits for the ISRT p -chart. Numerical results indicate that the ISRT p -chart can match any specific percentile point of run length distribution of the true limit of an unknown parameter. Therefore, we followed the concept of this chart construction in developing our proposed chart. Another chart was derived based on Wilson confidence interval and proposed by Park [21], called Wilson p -chart. Park compared the efficiencies of p -chart, a modified p -chart by Chen [14], and Wilson p -chart. Wilson p -chart outperformed the other charts for small nonconforming fractions. In this research, data is taken to be analyzed for a short period of time while the investigation process was in progress. This was the focus of this study, so the progressive charts, which often took historical data into account, were not investigated, which is not a disadvantage because most progressive charts are complex and difficult to use in practice. Therefore, the main objective of this research was to develop a method for improving p -chart. The secondary objective was to compare it to other kinds of existing control charts.

An attribute control chart for monitoring nonconforming fraction in a production process is proposed. It is called an improved Wald transformation p -chart (IWT p -chart). The proposed control limits were derived based on the square root transformation concept and adjusted Wald confidence interval estimation concept [20]. Agresti and Coull [20] reported that the interval estimation of the proportion parameter for binomial distribution performed well for both small proportion parameter and sample size. Therefore, the authors hope that the proposed control chart would be more sensitive in detecting out-of-control values for small nonconforming fractions in a manufacturing process (of which this situation occurs frequently in practice). In addition, the efficiency of the proposed chart was compared to those of ISRT p -chart, Wilson p -chart, and p -chart in terms of out-of-control average run length (ARL_1) and standard deviation of the run length ($SDRL$). The authors of Khoo et al. [22], Chen et al. [23], and Khilare and Shirke [24], compared performances in terms of ARL_1 and $SDRL$. They found that no matter which measure was used, the analysis results were not different. Our contribution to the field is our proposed IWT p -chart that can control nonconforming fractions in a production process with the best efficiency for large sample sizes and small nonconforming

fractions and outperforms several existing kinds of charts.

2. Materials and methods

This study proposes an IWT p -chart. In addition, its efficiency was compared to those of p -chart, ISRT p -chart and Wilson p -chart. These charts are explained below.

2.1. Nonconforming Fraction Control Chart (p-chart)

A well-known control chart for monitoring fractions of nonconforming was developed according to the general model of Shewhart [4]. It is called a nonconforming fraction control chart or p -chart. Let p be the fraction of nonconforming items of a process. Let X be the number of nonconforming items of the process that has a binomial distribution with parameters n and p (n is the sample size, and p is the nonconforming fraction). When the parameter p is known, the process can be monitored by plotting the sample nonconforming fractions $\hat{p}_i = \frac{X_i}{n}$, where $i = 1, 2, \dots, m$ on the p -chart with the center line, lower and upper control limits are given in Eq. (1).

$$\begin{aligned}
 CL_p &= p, & LCL_p &= p - L\sqrt{\frac{p(1-p)}{n}} & \text{and} & \\
 UCL_p &= p + L\sqrt{\frac{p(1-p)}{n}} & & & & (1)
 \end{aligned}$$

where L is the distance of the control limits from the center line. It is customary to choose $L = 3$ so that the in-control average run length (ARL_0) was 370.4 and the probability of type I error was 0.0027, i.e., an incorrect out-of-control signal or false alarm would be generated for only 27 out of 10,000 times. These limits are called three-sigma control limits. When the parameter p is unknown, it can be estimated by the mean of nonconforming fraction from the samples and denoted by symbol \bar{p} , where $\bar{p} = \frac{\sum_{i=1}^m \hat{p}_i}{m}$ and m is the number of samples with size n that are taken from the process.

2.2. Improved Square Root Transformation p-Chart (ISRT p-chart)

In 2006, a new attribute control chart, namely, an improved square root transformation p -chart or the ISRT p -chart was proposed [15]. A square root transformation was used to construct the lower and upper control limits of the ISRT p -chart. Let X be a binomial random variable with parameters n and p , where n is the sample size, and p is the nonconforming fraction of the process. The ISRT p -chart can be constructed with the center line as $CL_{ISRT_p} = f(p) = \sqrt{p}$. The lower (LCL_{ISRT_p}) and upper (UCL_{ISRT_p}) control lim-

its of the ISRT p -chart can be expressed as Eq. (2).

$$\begin{aligned}
 LCL_{ISRT_p} &= \sqrt{\bar{p}} - L \left(\frac{1}{2\sqrt{\bar{p}}} \right) \sqrt{\frac{p(1-p)}{n}} \\
 &\quad + \frac{1}{2} \left(-\frac{1}{4p\sqrt{\bar{p}}} \right) \left(\frac{9p(1-p)}{n} \right) \\
 &= \sqrt{\bar{p}} - \frac{L}{2} \sqrt{\frac{1-p}{n}} - \frac{9}{8} \left(\frac{1-p}{n\sqrt{\bar{p}}} \right) \\
 UCL_{ISRT_p} &= \sqrt{\bar{p}} + L \left(\frac{1}{2\sqrt{\bar{p}}} \right) \sqrt{\frac{p(1-p)}{n}} \\
 &\quad + \frac{1}{2} \left(-\frac{1}{4p\sqrt{\bar{p}}} \right) \left(\frac{4p(1-p)}{n} \right) \\
 &= \sqrt{\bar{p}} + \frac{L}{2} \sqrt{\frac{1-p}{n}} - \frac{1}{2} \left(\frac{1-p}{n\sqrt{\bar{p}}} \right)
 \end{aligned} \tag{2}$$

where L is the distance of the control limits from the center line. If three-sigma control limits are taken, then L equals 3 for asymptotically standard normal distribution. The parameter p can be estimated from the mean of nonconforming fractions in the samples and is denoted by symbol \bar{p} , where $\bar{p} = \frac{\sum_{i=1}^m \hat{p}_i}{m}$. The plot statistic of nonconforming fractions for the ISRT p -chart is given by $f(\hat{p}_i) = \sqrt{\frac{X_i}{n}}$, where X_i is the number of nonconforming items from the i^{th} subgroup for $i = 1, 2, \dots, m$, and n is the sample size.

2.3. Improved p-Chart Based on the Wilson Interval (Wilson p-chart)

In 2013, Park [21] proposed Wilson p -chart based on the Wilson confidence interval concept. Its performance is superior to those of several existing kinds of charts in terms of how close its coverage probabilities are to the given confidence coefficient [20]. It was found that Wilson p -chart outperformed the conventional p -chart and a modified p -chart proposed by Chen [14], especially for small values of nonconforming fractions. Let X_i be the number of nonconforming items in the i^{th} subgroup of sample size n from the production process, and let it have a binomial distribution with parameters n and p , where p is the nonconforming fraction of the process. When the parameter p is unknown, it can be estimated by the pooled mean of nonconforming fraction as $\bar{p} = \frac{\sum_{i=1}^m \hat{p}_i}{m}$, where m is the number of samples with size n that are taken from the process. The process can be monitored by plotting the sample nonconforming fractions $\hat{p}_i = \frac{X_i}{n}$, where $i = 1, 2, \dots, m$ on the Wilson p -chart. Then, plot the lower (LCL_{Wilson_p}) and upper (UCL_{Wilson_p}) control limits of the Wilson p -chart, which

can be expressed as Eqs. (3) and (4), respectively,

$$LCL_{Wilson\ p} = \frac{\bar{p} + k^2/(2N)}{1 + k^2/N} - \frac{k}{1 + k^2/N} \sqrt{\frac{\bar{p}(1 - \bar{p})}{n} + \frac{k^2}{4nN}} \tag{3}$$

$$UCL_{Wilson\ p} = \frac{\bar{p} + k^2/(2N)}{1 + k^2/N} + \frac{k}{1 + k^2/N} \sqrt{\frac{\bar{p}(1 - \bar{p})}{n} + \frac{k^2}{4nN}} \tag{4}$$

where $N = mn$. The target of ARL_0 was approximately 370.4, hence $k = 3$ was assigned for the construction of these control limits with the standard normal quantile.

2.4. Proposed Control Chart

The attribute control chart for nonconforming fraction of the process, namely, the improved Wald Transformation p -chart or IWT p -chart is proposed. This proposed chart was based on two concepts: the concept of transformation of ISRT p -chart and the concept of adjusted Wald confidence interval estimation [20]. Because a small nonconforming fraction (p) in binomial distribution often occurs in a process, the normal approximation of binomial distribution cannot approximate it adequately [15, 25–27]. Hence, an improved square root transformation procedure of Tsai et al. [15] was used to construct the proposed control chart. Furthermore, the efficiency of adjusted Wald confidence interval estimation of proportion parameter for the binomial distribution performed well for a small proportion parameter and a small sample size. Therefore, these two concepts were considered in finding the lower and upper limits of the proposed chart. Let a random variable X be the number of nonconforming items in a process that has a binomial distribution with parameters n and p , where n is a sample size and p is the nonconforming fraction. If most values of X are equal to 0, then the transformation in the form of \sqrt{X} is less accurate because the range of low-mean transformed values may be greater than the range of high-mean transformed values. Therefore, before applying the square root transformation of X , two successes and two failures for each sample was added to the dataset [20]. That is, the point estimator of p is given by $\hat{p}_{Adj} = \frac{X+2}{n+4}$, and this is the adjustable nonconforming fraction from the sample of size n .

Definition 1: Let $f(x)$ be a real-value function that is infinitely differentiable at point $x = a$, then the Taylor

series of function $f(x)$ at the point a is given by Eq. (5),

$$f(a) + \frac{f'(a)}{1!}(x - a) + \frac{f''(a)}{2!}(x - a)^2 + \frac{f'''(a)}{3!}(x - a)^3 + \dots = \sum_{n=0}^{\infty} \frac{f^{(n)}(a)}{n!}(x - a)^n \tag{5}$$

where $f^{(n)}(a)$ denotes the n^{th} derivative of f at the point a . The Taylor series of function $f(x)$ at the point $a = 0$ is called a Maclaurin series for $f(x)$ [28].

Theorem 1: Let X be the number of nonconforming items of a process that has a binomial distribution with parameters n and p . Let \hat{p}_{Adj} be the nonconforming fraction from the sample of size n . If $f(\hat{p}_{Adj}) = \sqrt{\hat{p}_{Adj}}$ is a function of the nonconforming fraction from the samples, then $\sqrt{n} \left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2} (\hat{p}_{Adj} - p)^2 \right]$ and $f'(p)\sqrt{n} (\hat{p}_{Adj} - p)$ have the same limit distribution.

Proof: Suppose $f(\hat{p}_{Adj}) = \sqrt{\hat{p}_{Adj}}$ is a function of the nonconforming fraction from samples of size n . By definition 1, using the Taylor series for function $f(\hat{p}_{Adj})$ to the second order at the point, $\hat{p}_{Adj} = p$, then $f(\hat{p}_{Adj})$ is given by

$$f(\hat{p}_{Adj}) \cong f(p) + f'(p) (\hat{p}_{Adj} - p) + \frac{f''(p)}{2} (\hat{p}_{Adj} - p)^2$$

or

$$f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2} (\hat{p}_{Adj} - p)^2 \cong f'(p) (\hat{p}_{Adj} - p)$$

Hence,

$$\sqrt{n} \left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2} (\hat{p}_{Adj} - p)^2 \right] \cong f'(p)\sqrt{n} (\hat{p}_{Adj} - p)$$

and $\sqrt{n} \left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2} (\hat{p}_{Adj} - p)^2 \right]$ and $f'(p)\sqrt{n} (\hat{p}_{Adj} - p)$ are the same formula and they have the same limit distribution.

Definition 2: Let X be a random variable that has a binomial distribution with parameters n and p . Then, x has an approximated normal distribution with a mean $E(X) = \mu = np$ and variance $V(X) = \sigma^2 = np(1 - p)$ for a sufficient large sample size and p close to 0.5 [29, 30].

By definition 2, the binomial distribution will tend to be positively or negatively skewed when np close to 0 or 1, but it will approximate a normal distribution for a large sample size [29].

Lemma 1: Let X be the number of nonconforming items of a process that has a binomial distribution with parameters n and p . For a sufficiently large sample size, the sampling distribution of $\hat{p}_{Adj} = \frac{X+2}{n+4}$ approximates a

normal distribution with a mean of $\mu_{\hat{p}_{Adj}} = \frac{np+2}{n+4}$ and a variance of $\sigma_{\hat{p}_{Adj}}^2 = \frac{np(1-p)}{(n+4)^2}$.

Proof: Suppose X is a random variable that has a binomial distribution with parameters n and p . The sample nonconforming fraction is given by $\hat{p}_{Adj} = \frac{X+2}{n+4}$. By definition 2, the mean and variance of \hat{p}_{Adj} can be derived as Eqs. (6) and (7), respectively,

$$\begin{aligned} \mu_{\hat{p}_{Adj}} &= E(\hat{p}_{Adj}) = E\left(\frac{X+2}{n+4}\right) = \frac{1}{n+4}E(X+2) \\ &= \frac{1}{n+4}\{E(X)+2\} = \frac{np+2}{n+4} \end{aligned} \tag{6}$$

$$\begin{aligned} \sigma_{\hat{p}_{Adj}}^2 &= V(\hat{p}_{Adj}) = V\left(\frac{X+2}{n+4}\right) = \frac{1}{(n+4)^2}V(X+2) \\ &= \frac{1}{(n+4)^2}V(X) = \frac{np(1-p)}{(n+4)^2} \end{aligned} \tag{7}$$

By the central limit theorem, the sampling distribution of $\hat{p}_{Adj} = \frac{X+2}{n+4}$ approximates a normal distribution with a mean of $\mu_{\hat{p}_{Adj}} = \frac{np+2}{n+4}$ and a variance of $\sigma_{\hat{p}_{Adj}}^2 = \frac{np(1-p)}{(n+4)^2}$ for a sufficiently large sample size.

Theorem 2: Let X be the number of nonconforming items of a process that has a binomial distribution with parameters n and p . The nonconforming fraction of a sample is expressed as $\hat{p}_{Adj} = \frac{X+2}{n+4}$. Since $f(p) = \sqrt{p}$, $f'(p)\sqrt{n}(\hat{p}_{Adj} - p)$ is approximately normally distributed with a mean of $\frac{f'(p)\sqrt{n}(np+2)}{n+4} - f'(p)\sqrt{np}$ and a variance of $\frac{[f'(p)]^2 n^2 p(1-p)}{(n+4)^2}$ for a sufficiently large sample size.

Proof: Suppose X is a random variable that has a binomial distribution with parameters n and p . The nonconforming fraction of a sample is given by $\hat{p}_{Adj} = \frac{X+2}{n+4}$ and $f(p) = \sqrt{p}$. By Lemma 1, $\hat{p}_{Adj} = \frac{X+2}{n+4}$ is approximately normally distributed with a mean of $E(\hat{p}_{Adj}) = \frac{np+2}{n+4}$ and a variance of $V(\hat{p}_{Adj}) = \frac{np(1-p)}{(n+4)^2}$ for a sufficiently large sample size. The mean and variance of $f'(p)\sqrt{n}(\hat{p}_{Adj} - p)$ are expressed as Eqs. (8) and (9), respectively,

$$\begin{aligned} E[f'(p)\sqrt{n}(\hat{p}_{Adj} - p)] &= f'(p)\sqrt{n}E(\hat{p}_{Adj} - p) \\ &= f'(p)\sqrt{n}\left[E(\hat{p}_{Adj}) - p\right] \\ &= f'(p)\sqrt{n}\left[\left\{\frac{np+2}{n+4}\right\} - p\right] \\ &= \frac{f'(p)\sqrt{n}(np+2)}{n+4} - f'(p)\sqrt{np} \end{aligned} \tag{8}$$

$$\begin{aligned} V[f'(p)\sqrt{n}(\hat{p}_{Adj} - p)] &= [f'(p)]^2 nV(\hat{p}_{Adj} - p) \\ &= [f'(p)]^2 nV(\hat{p}_{Adj}) \\ &= [f'(p)]^2 n\left[\frac{np(1-p)}{(n+4)^2}\right] \\ &= \frac{[f'(p)]^2 n^2 p(1-p)}{(n+4)^2} \end{aligned} \tag{9}$$

By the central limit theorem, the distribution of $f'(p)\sqrt{n}(\hat{p}_{Adj} - p)$ is approximately normally distributed with a mean of $\frac{f'(p)\sqrt{n}(np+2)}{n+4} - f'(p)\sqrt{np}$ and a variance of $\frac{[f'(p)]^2 n^2 p(1-p)}{(n+4)^2}$ for a sufficiently large sample size.

Theorem 3: Let $e = |\hat{p}_{Adj} - p|$ be the absolute error for the estimation of p with $\hat{p}_{Adj} = \frac{X+2}{n+4}$ and $f(p) = \sqrt{p}$. The center line and the lower and upper bounds of three-sigma control limits for the IWT p -chart are given by $CL_{IWTp} = f(p) = \sqrt{p}$,

$$\begin{aligned} LCL_{IWTp} &= \frac{\sqrt{p}}{2} - \frac{3\sqrt{n(1-p)}}{2(n+4)} + \frac{np+2}{2(n+4)\sqrt{p}} \\ &\quad - \frac{25n(1-p)}{8\sqrt{p}(n+4)^2} \end{aligned}$$

$$\begin{aligned} UCL_{IWTp} &= \frac{\sqrt{p}}{2} + \frac{3\sqrt{n(1-p)}}{2(n+4)} + \frac{np+2}{2(n+4)\sqrt{p}} \\ &\quad - \frac{2n(1-p)}{\sqrt{p}(n+4)^2} \end{aligned}$$

By theorem 3, the parameter p can be estimated as the mean of nonconforming fraction of a sample and denoted by symbol $\bar{p}_{Adj} = \frac{\sum_{i=1}^m \hat{p}_{Adj_i}}{m}$, where $\hat{p}_{Adj_i} = \frac{X_i+2}{n+4}$ for $i = 1, 2, \dots, m$. The plot statistic of nonconforming fraction for the IWT p -chart is given by $f(\hat{p}_{Adj_i}) = \sqrt{\frac{X_i+2}{n+4}}$, where X_i is the number of nonconforming items from the i th subgroup and n is the sample size.

Proof: Let $e = |\hat{p}_{Adj} - p|$ be the absolute error for the estimation of p with $\hat{p}_{Adj} = \frac{X+2}{n+4}$ and $f(p) = \sqrt{p}$. By Theorem 1 and Theorem 2, consider the standardized form of $f'(p)\sqrt{n}(\hat{p}_{Adj} - p)$ or $\sqrt{n}\left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2}(\hat{p}_{Adj} - p)^2\right]$. It is

$$\begin{aligned} Z &= \frac{(n+4)\sqrt{n}\left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2}e^2\right]}{|f'(p)|n\sqrt{p(1-p)}} \\ &\quad - \frac{(f'(p)\sqrt{n}(np+2) - (n+4)f'(p)\sqrt{np})}{|f'(p)|n\sqrt{p(1-p)}} \\ &= \frac{(n+4)\left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)}{2}e^2\right]}{|f'(p)|\sqrt{np(1-p)}} \\ &\quad - \frac{(np+2)}{\sqrt{np(1-p)}} + \frac{(n+4)p}{\sqrt{np(1-p)}} \end{aligned}$$

The distribution of $\frac{(n+4) \left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)e^2}{2} \right]}{|f'(p)|\sqrt{np(1-p)}} - \frac{np+2}{\sqrt{np(1-p)}} + \frac{(n+4)\sqrt{p}}{\sqrt{n(1-p)}}$ is asymptotically standard normal. The lower and upper bounds of three-sigma control limits for the IWT p -chart are taken as follows: $P(Z < -3) + P(Z > 3) = 0.0027$. That is,

$$P \left(\frac{(n+4) \left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)e^2}{2} \right]}{|f'(p)|\sqrt{np(1-p)}} - \frac{np+2}{\sqrt{np(1-p)}} + \frac{(n+4)\sqrt{p}}{\sqrt{n(1-p)}} < -3 \right) + P \left(\frac{(n+4) \left[f(\hat{p}_{Adj}) - f(p) - \frac{f''(p)e^2}{2} \right]}{|f'(p)|\sqrt{np(1-p)}} - \frac{np+2}{\sqrt{np(1-p)}} + \frac{(n+4)\sqrt{p}}{\sqrt{n(1-p)}} > 3 \right) = 0.0027 \tag{10}$$

Rearrange the terms in the two expressions of probabilities in Eq. (10) to get

$$P \left(f(\hat{p}_{Adj}) < f(p) - \frac{3|f'(p)|\sqrt{np(1-p)}}{n+4} + \frac{|f'(p)|(np+2)}{n+4} - |f'(p)|p + \frac{f''(p)e^2}{2} \right) + P \left(f(\hat{p}_{Adj}) > f(p) + \frac{3|f'(p)|\sqrt{np(1-p)}}{n+4} + \frac{|f'(p)|(np+2)}{n+4} - |f'(p)|p + \frac{f''(p)e^2}{2} \right) = 0.0027$$

Then, the IWT p -chart can be constructed with the center line as $CL_{IWTp} = f(p) = \sqrt{p}$. The first and second derivative of this function are $f'(p) = \frac{1}{2\sqrt{p}}$ and $f''(p) = -\frac{1}{4p\sqrt{p}}$, respectively. Then, the lower and upper bounds of three-sigma control limits for the IWT p -chart are given by Eqs. (11) and (12), respectively,

$$LCL_{IWTp} = f(p) - \frac{3|f'(p)|\sqrt{np(1-p)}}{n+4} + \frac{|f'(p)|(np+2)}{n+4} - |f'(p)|p + \frac{f''(p)e^2}{2} \tag{11}$$

$$UCL_{IWTp} = f(p) + \frac{3|f'(p)|\sqrt{np(1-p)}}{n+4} + \frac{|f'(p)|(np+2)}{n+4} - |f'(p)|p + \frac{f''(p)e^2}{2} \tag{12}$$

For a small nonconforming fraction p , the binomial distribution is positively skewed. Therefore, it is not appropriate to use the control limits with equal tails. After the numerical exploration on some cases of the small nonconforming fraction of $p < 0.1$ and $n \leq 1,000$, the absolute errors (e) for the estimation of p with $\hat{p}_{Adj} = \frac{X+2}{n+4}$ are suggested

to be $\frac{5\sqrt{np(1-p)}}{n+4}$ for the LCL_{IWTp} and $\frac{4\sqrt{np(1-p)}}{n+4}$ for the UCL_{IWTp} . Replacing the function of $f(p) = \sqrt{p}$ and its first and second derivatives with the recommended absolute errors in Eqs. (11) and (12), then the three-sigma of lower and upper control limits for the IWT p -chart are given by equations (13) and (14), respectively,

$$LCL_{IWTp} = \frac{\sqrt{p}}{2} - \frac{3\sqrt{n(1-p)}}{2(n+4)} + \frac{np+2}{2(n+4)\sqrt{p}} - \frac{25n(1-p)}{8\sqrt{p}(n+4)^2} \tag{13}$$

$$UCL_{IWTp} = \frac{\sqrt{p}}{2} + \frac{3\sqrt{n(1-p)}}{2(n+4)} + \frac{np+2}{2(n+4)\sqrt{p}} - \frac{2n(1-p)}{\sqrt{p}(n+4)^2} \tag{14}$$

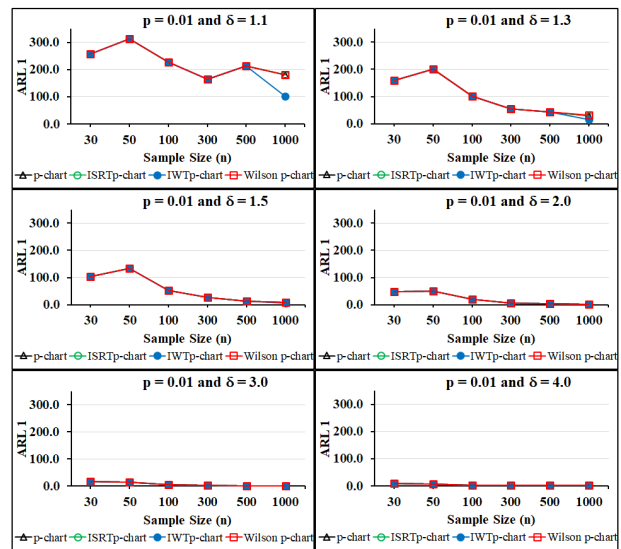


Fig. 1. Estimates of ARL_1 for four control charts in the case of $p_0 = 0.01$ and different shifts of nonconforming fraction

3. Results of the simulation study

The performances of the four control charts were compared via a simulation study. The nonconforming count data (X_i) were generated in the form of a binomial distribution with two parameters that are set as follows: five levels of nonconforming fraction for in-control process (p_0) are set as 0.01, 0.02, 0.05, 0.07, and 0.09 ; six levels of sample size (n) are set as 30, 50, 100, 300, 500, and 1000. In addition, the subgroup size (m) was defined as 25 . For an out-of-control process, the shift in nonconforming fraction in the production process (δ) were set as 1.1, 1.3, 1.5, 2.0, 3.0, and 4.0 for $p_1 = p_0\delta$, where p_1 was the nonconforming fraction of an out-of-control process. The ARL_0 of all control

Table 1. Estimates of ARL_1 and $SDRL$ for four control charts in the case of $p_0 = 0.01$

n	δ	p-chart		ISRT p-chart		Wilson p-chart		IWT p-chart	
		ARL1	SDRL	ARL1	SDRL	ARL1	SDRL	ARL1	SDRL
30	1.1	256.410	255.910	256.410	255.910	256.410	255.910	256.410	255.910
	1.3	158.730	158.229	158.730	158.229	158.730	158.229	158.730	158.229
	1.5	103.093	102.592	103.093	102.592	103.093	102.592	103.093	102.592
	2	47.847	47.344	47.847	47.344	47.847	47.344	47.847	47.344
	3	16.667	16.159	16.667	16.159	16.667	16.159	16.667	16.159
	4	8.569	8.053	8.569	8.053	8.569	8.053	8.569	8.053
50	1.1	312.500	312.000	312.500	312.000	312.500	312.000	312.500	312.000
	1.3	200.000	199.499	200.000	199.499	200.000	199.499	200.000	199.499
	1.5	133.333	132.832	133.333	132.832	133.333	132.832	133.333	132.832
	2	50.000	49.497	50.000	49.497	50.000	49.497	50.000	49.497
	3	15.456	14.948	15.456	14.948	15.456	14.948	15.456	14.948
	4	7.128	6.609	7.128	6.609	7.128	6.609	7.128	6.609
100	1.1	227.273	226.772	227.273	226.772	227.273	226.772	227.273	226.772
	1.3	102.041	101.540	102.041	101.540	102.041	101.540	102.041	101.540
	1.5	52.356	51.854	52.356	51.854	52.356	51.854	52.356	51.854
	2	19.305	18.798	19.305	18.798	19.305	18.798	19.305	18.798
	3	5.609	5.084	5.609	5.084	5.609	5.084	5.609	5.084
	4	2.714	2.156	2.714	2.156	2.714	2.156	2.714	2.156
300	1.1	163.934	163.434	163.934	163.434	163.934	163.434	163.934	163.434
	1.3	55.556	55.053	55.556	55.053	55.556	55.053	55.556	55.053
	1.5	25.974	25.469	25.974	25.469	25.974	25.469	25.974	25.469
	2	6.716	6.196	6.716	6.196	6.716	6.196	6.716	6.196
	3	1.841	1.245	1.841	1.245	1.841	1.245	1.841	1.245
	4	1.176	0.455	1.176	0.455	1.176	0.455	1.176	0.455
500	1.1	212.766	212.265	212.766	212.265	212.766	212.265	212.766	212.265
	1.3	43.668	43.165	43.668	43.165	43.668	43.165	43.668	43.165
	1.5	14.045	13.536	14.045	13.536	14.045	13.536	14.045	13.536
	2	3.113	2.565	3.113	2.565	3.113	2.565	3.113	2.565
	3	1.212	0.507	1.212	0.507	1.212	0.507	1.212	0.507
	4	1.027	0.167	1.027	0.167	1.027	0.167	1.027	0.167
1000	1.1	181.818	181.318	181.818	181.318	181.818	181.318	102.041	101.540
	1.3	28.818	28.314	28.818	28.314	30.769	30.265	16.447	15.940
	1.5	8.143	7.627	8.143	7.627	8.382	7.866	5.414	4.889
	2	1.812	1.213	1.812	1.213	1.831	1.234	1.559	0.934
	3	1.025	0.159	1.025	0.159	1.027	0.165	1.016	0.129
	4	1.001	0.022	1.001	0.022	1.000	0.017	1.000	0.010

charts was set at 370.4 because the proposed chart (IWT p -chart) was derived based only on three-sigma control limits. The details of the proof are in Theorem 3. Therefore, in the data simulation, the efficiency comparison of three-sigma control limits was investigated. In many past studies, it was found that most chart performance comparisons gave the same analytical results regardless of the level of the ARL_0 used [12]. Therefore, the performance comparison of the four control charts tested in this study focused on ARL_1 and $SDRL$ of three sigma control to determine which chart will have the most sensitive ability to detect process changes. This simulation study was conducted with a Monte Carlo technique for 180 situations and repeated 10,000 times for each situation. The perfor-

mance comparison measures were the estimates of ARL_1 and $SDRL$. The control chart with the lowest ARL_1 and $SDRL$ was the most effective chart for detection of the shift in the process. The simulation results are shown in Tables 1 to 5. Table 1 shows that the efficiencies of all control charts tend to be the same for $p_0 = 0.01$ and sample sizes of 30, 50, 100, 300 and 500 . However, the IWT p -chart was distinctly the most efficient for detecting all the shifts in nonconforming fraction with a large sample size of 1000. In addition, the ARL_1 s and $SDRL$ s of all control charts tended to decrease when the sample sizes and the shift in nonconforming fraction increased. Especially for a very large shift in nonconforming fraction of 4.0 and large sample size of 1000, the ARL_1 s and $SDRL$ s of all control charts were

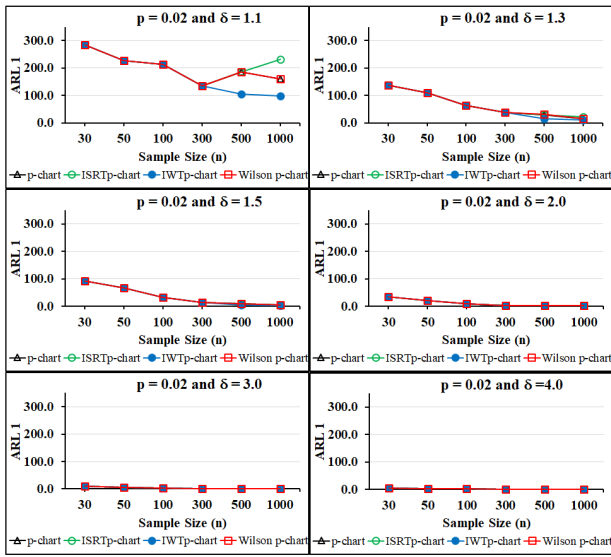


Fig. 2. Estimates of ARL_1 for four control charts in the case of $p_0 = 0.02$ and different shifts of nonconforming fraction

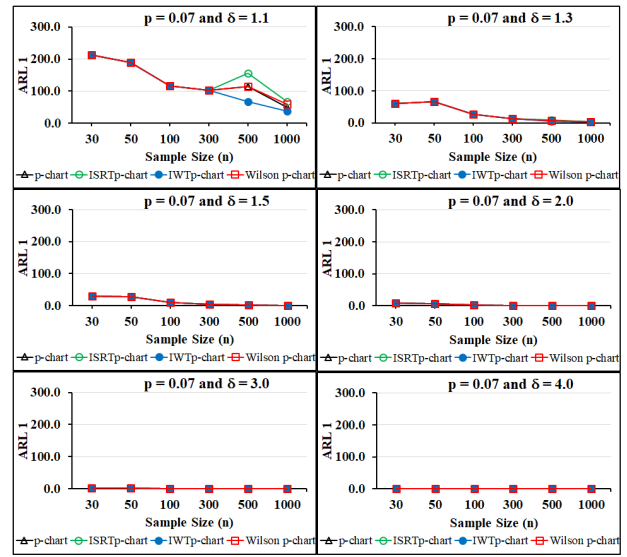


Fig. 4. Estimates of ARL_1 for four control charts in the case of $p_0 = 0.07$ and different shifts of nonconforming fraction

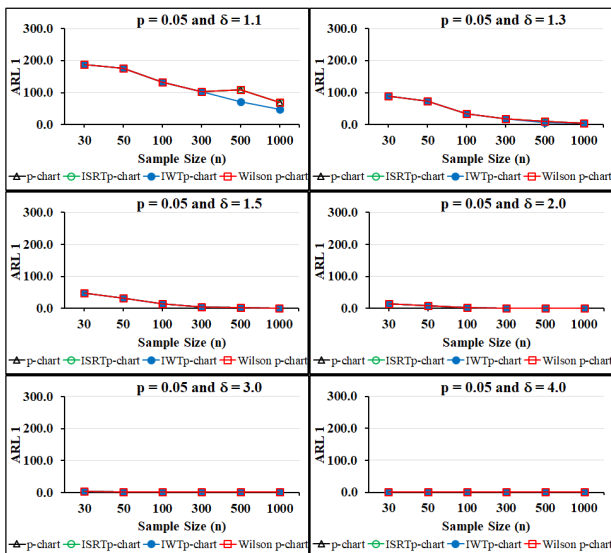


Fig. 3. Estimates of ARL_1 for four control charts in the case of $p_0 = 0.05$ and different shifts of nonconforming fraction

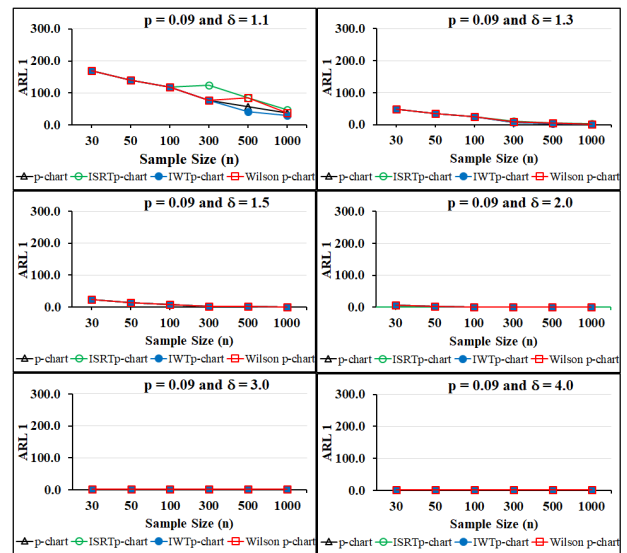


Fig. 5. Estimates of ARL_1 for four control charts in the case of $p_0 = 0.09$ and different shifts of nonconforming fraction

close to 1 and 0, respectively. Tables 2 to 5 show that the efficiencies of all control charts were the same for p_0 equals to 0.02, 0.05, 0.07, and 0.09 and sample sizes of 30, 50, 100, and 300. Moreover, the IWT p -chart was the most efficient for sample sizes of 500 and 1000, especially for a small shift in nonconforming fraction. For a large sample size of 1000 and a small shift in nonconforming fraction, the ability of ISRT p -chart to detect an out-of-control process was relatively poor compared to the other three charts. Further, the ARL_1 s and $SDRL$ s of all control charts tended to decrease when the sample size and the shift in nonconforming frac-

tion increased. That is, the ARL_1 s and $SDRL$ s of all control charts tend to be 1 and 0, respectively for a large shift in nonconforming fraction and sample sizes of 300, 500, and 1000.

Figs. 1 to 5 show that the ARL_1 s of all control charts, when the sample size increased, tended to decrease rapidly for a small level of the shift in nonconforming fraction, for $p_0 = 0.01, 0.02, 0.05, 0.07,$ and 0.09 . In addition, the proposed IWT p -chart was the most efficient for large sample sizes of 500 and 1000, especially for a small shift in the nonconforming fraction, such as $\delta = 1.1$, in this simulation

Table 2. Estimates of ARL_1 and $SDRL$ for four control charts in the case of $p_0 = 0.02$

n	δ	p-chart		ISRT p -chart		Wilson p -chart		IWT p -chart	
		ARL1	SDRL	ARL1	SDRL	ARL1	SDRL	ARL1	SDRL
30	1.1	285.714	285.214	285.714	285.214	285.714	285.214	285.714	285.214
	1.3	136.986	136.485	136.986	136.485	136.986	136.485	136.986	136.485
	1.5	90.909	90.408	90.909	90.408	90.909	90.408	90.909	90.408
	2	34.722	34.219	34.722	34.219	34.722	34.219	34.722	34.219
	3	9.823	9.310	9.823	9.310	9.823	9.310	9.823	9.310
	4	4.710	4.181	4.710	4.181	4.710	4.181	4.710	4.181
50	1.1	227.273	226.772	227.273	226.772	227.273	226.772	227.273	226.772
	1.3	109.890	109.389	109.890	109.389	109.890	109.389	109.890	109.389
	1.5	66.667	66.165	66.667	66.165	66.667	66.165	66.667	66.165
	2	21.231	20.725	21.231	20.725	21.231	20.725	21.231	20.725
	3	5.731	5.207	5.731	5.207	5.731	5.207	5.731	5.207
	4	2.690	2.132	2.690	2.132	2.690	2.132	2.690	2.132
100	1.1	212.766	212.265	212.766	212.265	212.766	212.265	212.766	212.265
	1.3	63.291	62.789	63.291	62.789	63.291	62.789	63.291	62.789
	1.5	31.646	31.142	31.646	31.142	31.646	31.142	31.646	31.142
	2	9.470	8.956	9.470	8.956	9.470	8.956	9.470	8.956
	3	2.559	1.997	2.559	1.997	2.559	1.997	2.559	1.997
	4	1.428	0.781	1.428	0.781	1.428	0.781	1.428	0.781
300	1.1	135.135	134.634	135.135	134.634	135.135	134.634	135.135	134.634
	1.3	39.370	38.867	39.370	38.867	39.370	38.867	39.370	38.867
	1.5	14.535	14.026	14.535	14.026	14.535	14.026	14.535	14.026
	2	3.169	2.621	3.169	2.621	3.169	2.621	3.169	2.621
	3	1.160	0.430	1.160	0.430	1.160	0.430	1.160	0.430
	4	1.009	0.094	1.009	0.094	1.009	0.094	1.009	0.094
500	1.1	185.185	184.685	185.185	184.685	185.185	184.685	106.383	105.882
	1.3	29.326	28.821	29.326	28.821	31.447	30.942	16.000	15.492
	1.5	8.217	7.701	8.217	7.701	8.511	7.995	5.565	5.040
	2	1.835	1.238	1.835	1.238	1.830	1.232	1.575	0.951
	3	1.025	0.159	1.025	0.159	1.025	0.161	1.015	0.123
	4	1.000	0.017	1.000	0.017	1.000	0.010	1.000	0.010
1000	1.1	161.290	160.790	232.558	232.058	161.290	160.790	98.039	97.538
	1.3	14.837	14.328	22.779	22.273	14.837	14.328	10.309	9.797
	1.5	3.876	3.339	4.960	4.432	3.876	3.339	3.086	2.538
	2	1.171	0.447	1.229	0.530	1.171	0.447	1.125	0.375
	3	1.000	0.000	1.000	0.010	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000

study.

4. Real-life application

A real-life data set for the three-sigma control limits construction of four charts-IWT p -chart, p -chart, ISRT p -chart and Wilson p -chart-was taken from Montgomery [4]. It was related to a production process of orange juice which was packed in 6 -ounce cardboard cans. These cans are inspected for possible non-compliance, such as leaks in the side seams or at the bottom joint. Cans that do not meet these requirements may have improper sealing at the side seams or bottom panel. These four control charts can be used to improve the fraction of nonconforming cans produced by this process. To establish these, samples of

50 cans were randomly drawn to check the quality over a period of half an hour over the course of three shifts in which the machine was continuously running. Data were collected from a total of 30 subgroups. The information is shown in Table 6.

The initial control limits of four control charts for the data in Table 6 are shown in Fig. 6. The plot statistics for each chart from the initial subgroup are plotted on these charts. Fig. 6 shows that there are two points from subgroups 15 and 23 that are above the upper control limits for all control charts. These points had to be investigated to see whether an assignable cause can be determined. The inspection revealed that a new batch of cardboard stock had been produced during that half-hour period in sub-

Table 3. Estimates of ARL_1 and SDRL for four control charts in the case of $p_0 = 0.05$

n	δ	p -chart		ISRT p -chart		Wilson p -chart		IWT p -chart	
		ARL1	SDRL	ARL1	SDRL	ARL1	SDRL	ARL1	SDRL
30	1.1	188.679	188.179	188.679	188.179	188.679	188.179	188.679	188.179
	1.3	88.496	87.994	88.496	87.994	88.496	87.994	88.496	87.994
	1.5	47.619	47.116	47.619	47.116	47.619	47.116	47.619	47.116
	2	13.870	13.360	13.870	13.360	13.870	13.360	13.870	13.360
	3	3.461	2.919	3.461	2.919	3.461	2.919	3.461	2.919
	4	1.751	1.146	1.751	1.146	1.751	1.146	1.751	1.146
50	1.1	175.439	174.938	175.439	174.938	175.439	174.938	175.439	174.938
	1.3	74.074	73.572	74.074	73.572	74.074	73.572	74.074	73.572
	1.5	33.445	32.941	33.445	32.941	33.445	32.941	33.445	32.941
	2	8.231	7.714	8.231	7.714	8.231	7.714	8.231	7.714
	3	2.064	1.482	2.064	1.482	2.064	1.482	2.064	1.482
	4	1.236	0.540	1.236	0.540	1.236	0.540	1.236	0.540
100	1.1	133.333	132.832	133.333	132.832	133.333	132.832	133.333	132.832
	1.3	33.333	32.829	33.333	32.829	33.333	32.829	33.333	32.829
	1.5	14.144	13.635	14.144	13.635	14.144	13.635	14.144	13.635
	2	3.413	2.870	3.413	2.870	3.413	2.870	3.413	2.870
	3	1.194	0.481	1.194	0.481	1.194	0.481	1.194	0.481
	4	1.013	0.115	1.013	0.115	1.013	0.115	1.013	0.115
300	1.1	103.093	102.592	103.093	102.592	103.093	102.592	103.093	102.592
	1.3	18.248	17.741	18.248	17.741	18.248	17.741	18.248	17.741
	1.5	5.465	4.939	5.465	4.939	5.465	4.939	5.465	4.939
	2	1.343	0.679	1.343	0.679	1.343	0.679	1.343	0.679
	3	1.001	0.025	1.001	0.025	1.001	0.025	1.001	0.025
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
500	1.1	109.890	109.389	109.890	109.389	109.890	109.389	71.429	70.927
	1.3	9.718	9.205	9.718	9.205	9.718	9.205	7.067	6.548
	1.5	2.717	2.160	2.717	2.160	2.717	2.160	2.313	1.743
	2	1.059	0.251	1.059	0.251	1.059	0.251	1.045	0.216
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1000	1.1	68.966	68.464	68.966	68.464	68.966	68.464	47.847	47.344
	1.3	4.148	3.613	4.148	3.613	4.148	3.613	3.511	2.969
	1.5	1.416	0.768	1.416	0.768	1.416	0.768	1.339	0.674
	2	1.001	0.026	1.001	0.026	1.001	0.026	1.000	0.020
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000

group of 15, and there is a reasonable ground to believe that assignable cause had also occurred here. Additionally, subgroup 23's inexperienced operator was temporarily assigned to the machine and this may cause a high fraction of non-conforming cans from that subgroup. Therefore, samples from subgroups 15 and 23 were eliminated and the new control limits of the four control charts are shown in Table 7.

The plot statistics for the revised control limits of p -chart and Wilson p -chart are given by the nonconforming fraction of a sample or $\hat{p}_i = \frac{X_i}{n}$, but those for ISRT p -chart and IWT p -chart are $f(\hat{p}_i) = \sqrt{\frac{X_i}{n}}$ and $f(\hat{p}_{Adj_i}) = \sqrt{\frac{X_i+2}{n+4}}$, respectively. Although the proportion of nonconforming cans in subgroup 21 was still outside the upper control

limits of three charts, namely p -chart, Wilson p -chart and IWT p -chart, there was no effect of an assignable cause. Therefore, the data in subgroup 21 were retained and those revised control limits in Table 7 were applied for further production control process.

5. Discussions

In this research, the efficiency of IWT p -chart was compared with these of p -chart, ISRT p -chart, and Wilson p -chart via a simulation study. It was found that the sensitivity to detect an out-of-control process of IWT p -chart tended to be better than the other two charts for a small nonconforming fraction in the process because the proposed chart was derived from a transformation concept of Tsai et al. [15]

Table 4. Estimates of ARL_1 and $SDRL$ for four control charts in the case of $p_0 = 0.07$

n	δ	p-chart		ISRT p -chart		Wilson p -chart		IWT p -chart	
		ARL1	SDRL	ARL1	SDRL	ARL1	SDRL	ARL1	SDRL
30	1.1	212.766	212.265	212.766	212.265	212.766	212.265	212.766	212.265
	1.3	60.606	60.104	60.606	60.104	60.606	60.104	60.606	60.104
	1.5	29.762	29.258	29.762	29.258	29.762	29.258	29.762	29.258
	2	8.718	8.203	8.718	8.203	8.718	8.203	8.718	8.203
	3	2.243	1.669	2.243	1.669	2.243	1.669	2.243	1.669
	4	1.283	0.602	1.283	0.602	1.283	0.602	1.283	0.602
50	1.1	188.679	188.179	188.679	188.179	188.679	188.179	188.679	188.179
	1.3	67.114	66.612	67.114	66.612	67.114	66.612	67.114	66.612
	1.5	28.169	27.664	28.169	27.664	28.169	27.664	28.169	27.664
	2	6.460	5.939	6.460	5.939	6.460	5.939	6.460	5.939
	3	1.583	0.960	1.583	0.960	1.583	0.960	1.583	0.960
	4	1.076	0.285	1.076	0.285	1.076	0.285	1.076	0.285
100	1.1	116.279	115.778	116.279	115.778	116.279	115.778	116.279	115.778
	1.3	27.322	26.818	27.322	26.818	27.322	26.818	27.322	26.818
	1.5	10.122	9.608	10.122	9.608	10.122	9.608	10.122	9.608
	2	2.339	1.769	2.339	1.769	2.339	1.769	2.339	1.769
	3	1.050	0.229	1.050	0.229	1.050	0.229	1.050	0.229
	4	1.001	0.025	1.001	0.025	1.001	0.025	1.001	0.025
300	1.1	103.093	102.592	103.093	102.592	103.093	102.592	103.093	102.592
	1.3	13.280	12.770	13.280	12.770	13.193	12.683	13.280	12.770
	1.5	3.592	3.051	3.592	3.051	3.635	3.095	3.592	3.051
	2	1.116	0.359	1.116	0.359	1.117	0.361	1.116	0.359
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	1.1	114.943	114.441	156.250	155.749	114.943	114.441	66.225	65.723
500	1.3	7.174	6.655	9.470	8.956	7.062	6.543	5.631	5.106
	1.5	2.006	1.420	2.253	1.680	1.966	1.378	1.786	1.185
	2	1.013	0.116	1.018	0.135	1.013	0.113	1.010	0.098
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1000	1.1	49.261	48.759	66.667	66.165	58.480	57.977	37.594	37.091
	1.3	2.848	2.294	3.204	2.657	2.848	2.294	2.538	1.976
	1.5	1.158	0.428	1.194	0.481	1.162	0.433	1.127	0.377
	2	1.000	0.010	1.000	0.010	1.000	0.000	1.000	0.010
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000

and adjusted Wald confidence interval estimation concept. These two concepts tend to be performed well efficiency of inference for a low level of nonconforming fraction as a result of zero nonconforming items in the favorite process [13, 20]. The out-of-control average run length and standard deviation of the run length tended to decrease when the sample size and the shift of nonconforming fraction increased, agreeing with the results of Sinsomboonthong and Sinsomboonthong [5], Rod-o et al. [13], Tsai et al. [15], and Aslam et al. [31]. The ISRT p -chart tended to have a good efficiency for a large shift in nonconforming fraction and large sample size, agreeing with Sukparungsee [12] and Tsai et al. [15]. The strength of the proposed chart is its effectiveness in fast-detecting abnormalities in the process

even if the nonconforming fraction slightly changes from the target during that time. Moreover, the proposed chart does not have complicated formulas and so easy to apply in real life. In addition, the proposed chart only considers the data collected during a short period of production time, a true reflection of the actual production process.

6. Conclusions

In this research, the efficiencies or the out-of-control process detection sensitivity of four charts- p -chart, ISRT p -chart, Wilson p -chart and IWT p -chart-were compared. The comparison was especially for the case of low nonconforming rate commonly occurred in a manufacturing process. The appropriate nonconforming fraction control charts for each

Table 5. Estimates of ARL_1 and SDRL for four control charts in the case of $p_0 = 0.09$

n	δ	p-chart		ISRT p -chart		Wilson p -chart		IWT p -chart	
		ARL1	SDRL	ARL1	SDRL	ARL1	SDRL	ARL1	SDRL
30	1.1	169.492	168.991	169.492	168.991	169.492	168.991	169.492	168.991
	1.3	49.505	49.002	49.505	49.002	49.505	49.002	49.505	49.002
	1.5	24.450	23.945	24.450	23.945	24.450	23.945	24.450	23.945
	2	6.382	5.860	6.382	5.860	6.382	5.860	6.382	5.860
	3	1.699	1.089	1.699	1.089	1.699	1.089	1.699	1.089
	4	1.112	0.352	1.112	0.352	1.112	0.352	1.112	0.352
50	1.1	140.845	140.344	140.845	140.344	140.845	140.344	140.845	140.344
	1.3	35.587	35.084	35.587	35.084	35.587	35.084	35.587	35.084
	1.5	14.993	14.484	14.993	14.484	14.993	14.484	14.993	14.484
	2	3.610	3.070	3.610	3.070	3.610	3.070	3.610	3.070
	3	1.204	0.495	1.204	0.495	1.204	0.495	1.204	0.495
	4	1.012	0.112	1.012	0.112	1.012	0.112	1.012	0.112
100	1.1	117.647	117.146	117.647	117.146	117.647	117.146	117.647	117.146
	1.3	25.126	24.621	25.126	24.621	25.126	24.621	25.126	24.621
	1.5	8.190	7.674	8.190	7.674	8.190	7.674	8.190	7.674
	2	1.840	1.243	1.840	1.243	1.840	1.243	1.840	1.243
	3	1.013	0.113	1.013	0.113	1.013	0.113	1.013	0.113
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
300	1.1	76.336	75.834	76.336	75.834	76.336	75.834	76.336	75.834
	1.3	7.975	7.458	7.975	7.458	8.231	7.714	7.975	7.458
	1.5	2.358	1.789	2.358	1.789	2.391	1.824	2.358	1.789
	2	1.025	0.160	1.025	0.160	1.027	0.167	1.025	0.160
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
500	1.1	56.180	55.678	85.470	84.969	85.470	84.969	41.322	40.819
	1.3	4.198	3.664	5.051	4.523	5.051	4.523	3.552	3.011
	1.5	1.432	0.786	1.526	0.895	1.526	0.895	1.346	0.683
	2	1.001	0.033	1.002	0.042	1.002	0.042	1.001	0.028
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
1000	1.1	37.594	37.091	46.948	46.446	37.594	37.091	29.851	29.346
	1.3	2.088	1.507	2.271	1.699	2.064	1.482	1.917	1.326
	1.5	1.054	0.239	1.066	0.264	1.053	0.235	1.045	0.216
	2	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	3	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000
	4	1.000	0.000	1.000	0.000	1.000	0.000	1.000	0.000

of 180 situations are shown in Table 8.

Table 8 shows that the proposed IWT p -chart tended to perform with the best efficiency for large sample sizes of 500 and 1000 and the level of nonconforming fraction below 0.1 whatever the shift in nonconforming fraction was. However, for a smaller sample size, $n < 500$, the IWT p -chart provided the same efficiency as the p -chart and ISRT p -chart and Wilson p -chart. The out-of-control average run length had a downward trend for an increase in sample size and shift of nonconforming fraction.

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Table 6. Data for nonconforming cans produced in the process

Subgroup number	Number of nonconforming cans (X_i)	Subgroup number	Number of nonconforming cans (X_i)	Subgroup number	Number of nonconforming cans (X_i)
1	12	11	5	21	20
2	15	12	6	22	18
3	8	13	17	23	24
4	10	14	12	24	15
5	4	15	22	25	9
6	7	16	8	26	12
7	16	17	10	27	7
8	9	18	5	28	13
9	14	19	13	29	9
10	10	20	11	30	6

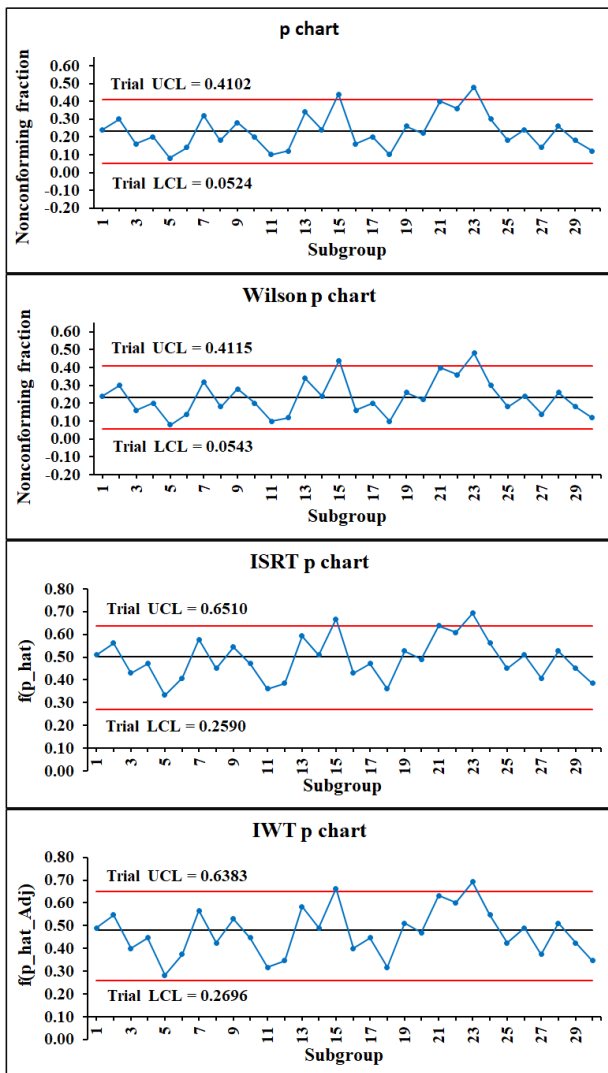


Fig. 6. Initial control limits of four control charts for data in Table 6

Table 7. Revised control limits of four control charts

Control chart	Lower control limit	Upper control limit
p -chart	0.0407	0.3893
Wilson p -chart	0.0428	0.3908
ISRT p -chart	0.2376	0.6347
IWT p -chart	0.2501	0.6238

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Table 8. Appropriate nonconforming fraction control chart(s) for each situation

n	δ	Nonconforming fraction of in-control process (p_0)				
		0.01	0.02	0.05	0.07	0.09
30	1.1	All	All	All	All	All
	1.3	All	All	All	All	All
	1.5	All	All	All	All	All
	2.0	All	All	All	All	All
	3.0	All	All	All	All	All
	4.0	All	All	All	All	All
50	1.1	All	All	All	All	All
	1.3	All	All	All	All	All
	1.5	All	All	All	All	All
	2.0	All	All	All	All	All
	3.0	All	All	All	All	All
	4.0	All	All	All	All	All
100	1.1	All	All	All	All	All
	1.3	All	All	All	All	All
	1.5	All	All	All	All	All
	2.0	All	All	All	All	All
	3.0	All	All	All	All	All
	4.0	All	All	All	All	All
300	1.1	All	All	All	All	All
	1.3	All	All	All	All	All
	1.5	All	All	All	All	All
	2.0	All	All	All	All	All
	3.0	All	All	All	All	All
	4.0	All	All	All	All	All
500	1.1	All	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	1.3	All	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	1.5	All	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	2.0	All	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	3.0	All	IWT p -chart	All	All	All
	4.0	All	IWT p -chart	All	All	All
1000	1.1	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	1.3	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	1.5	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart	IWT p -chart
	2.0	IWT p -chart	IWT p -chart	IWT p -chart	All	All
	3.0	IWT p -chart	All	All	All	All
	4.0	IWT p -chart	All	All	All	All

Note: Let "All" be the IWT p -chart, p -chart, ISRT p -chart and Wilson p -chart

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