# The Effect of Non-Normality and Measurement Error on the Economic Design of $\bar{X}$ Control Chart 

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#### Abstract

An attempt is made to determine the effect of non-normality and measurement error on the economic design of $\bar{X}$ control chart. For non-normal population, we have considered the first four terms of an Edgeworth series. As one will be interested in having a suitable economic control chart under measurement error for non-normal variables, the optimum values of sample size $n$ and sampling interval $h$ are determined for different values of $k$.


Keywords: Non-normality $\bar{X}$, control chart, Edgeworth series, Measurement error

## 1. Introduction

Traditionally, when designing control charts, one usually assumes that the measurements in the sample are normally distributed. However, this assumption may not be tenable. If the measurements really are normally distributed, then the statistic $\bar{x}$ is also normally distributed. If the measurements are asymmetrically distributed, then the statistic $\bar{x}$ will be approximately normally distributed only when the sample size $n$ is sufficiently large (based on the central limit theorem). Unfortunately, when a control chart is applied to monitor the process, the sample size $n$ is never sufficiently large due to the sampling cost. Therefore, if the measurements are not normally distributed, the traditional way of designing a control chart may reduce the ability of the control chart to detect the assignable causes. Yourstone and Zimmer (1992) used the Burr distribution to represent various non-normal distributions and, consequently, to statistically design the control limits of an control chart. However, they did not consider cost in the design of the chart. In designing a control chart, three parameters - the sample size $n$, time $h$ between successive samples, and the number $k$ of standard deviations away from the center line must be determined. In economic-statistical design, the three parameters are chosen so that the expected cost per hour is minimized under constraints, e.g., minimum allowable values of Type I error probability (probability that point falls outside control limits while the process is in control) and Type II error probability (probability that point falls within control limits while out of control). Saniga (1989) first proposes the economic-statistical design. Al-Oraini and Rahim (2003) have shown that the statistical performance can be improved by the economic-statistical design significantly with only a slight increase in the cost. Kanazuka (1986) used to study the effect of measurement error on the performance of an $\overline{\boldsymbol{X}} \boldsymbol{-} \boldsymbol{R}$ chart. Mittag (1995) and Mittag and Stemann (1998) investigated how the measurement error affects the $\overline{\boldsymbol{X}}-\boldsymbol{S}$ chart. Linna and Woodall (2001) assumed a linear relationship between the surrogate and the true quality characteristics to study the effect of measurement error on the performance of $\bar{X}$ and $S^{2}$ charts. However, the general practice to set symmetrical control limits for the mean to detect shifts in the process average when the process variation remain constant. The
determination at $k$ is mainly based upon the level of the control desired in a given situation depending upon the market price of defectives and effectives.

## 2. Mathematical Model for Cost Function

Duncan (1956) obtained an approximate function for the average net income per hour of using the control chart for mean of normal variables as :
$I=\left[V_{0}\right]-\frac{\eta \mu B+(\alpha T / h)+\eta W}{1+\eta B}-\frac{b+c n}{h}$
where
$V_{0}=$ the average income per hour when the process is in control and the process average is $\mu$,
$V_{l}=$ the average income per hour when the process is not in control and the process average is $\mu^{\prime}=\mu+\delta \sigma$,
$M=V_{0}-V_{1}$,
$\eta$ = the average number of times the assignable causes occur within an interval of time,
$B=a h+C n+D$,
$a=\frac{1}{P}-\frac{1}{2}+\frac{\eta h}{12}$,
$h=$ interval between sampling in hours,
$C n=$ the time required to take and inspect a sample of size $n$,
$D=$ average time taken to find the assignable cause after a point plotted on the chart falls out side the control limits, $P=$ probability of detecting an assignable cause when it exists;
$=\int_{-\infty}^{\mu-k \sigma / \sqrt{n}} g\left(\bar{x} / \mu^{\prime}\right) d \bar{x}+\int_{\mu+k \sigma / \sqrt{n}}^{\infty} g\left(\bar{x} / \mu^{\prime}\right) d \bar{x}$
$\cong 1-\Phi(k-\delta \sqrt{n}) \quad$ for $\delta>0$,
where $g(\bar{x} / \mu)$ is the density function of $\bar{x}$ when the true mean is $\mu$ and $\Phi(x)$ is the normal probability integral,
$\alpha=$ probability of wrongly indicating the presence of assignable causes,
$=\int_{\mu-k \sigma / \sqrt{n}}^{\mu+k \sigma / \sqrt{n}} g(\bar{x} / \mu) d \bar{x}$
$=2 \Phi(-k)$
$=\alpha_{N}$.
$T=$ the cost per occasion of looking for an assignable cause when no assignable cause exists,
$W=$ the average cost per occasion of finding the assignable when it exists,
$b=$ per sample cost of sampling and plotting, that is independent of sample size,
and $c=$ the cost per unit of measuring an item in a sample.
The average cost per hour involved for maintaining the control chart is $(b+c n) / h$. The average net income per
hour of the process under the surveillance of the control chart for mean can be rewritten as,

$$
I=V_{0}-L
$$

where

$$
L=\frac{\eta M B+(\alpha T / h)+\eta B}{1+\eta B}+\frac{b+c n}{h}
$$

$L$ can now be treated as the per hour cost due to the surveillance of the process under the control chart. The probability density function for non-normal population is represented by first four terms of Edgeworth series and $\dot{P}$ and $\alpha^{\prime}$ are determined from the sampling distribution of mean and are written as,

$$
\begin{align*}
P^{\prime}= & 1-\Phi(\xi)+\frac{\lambda_{3}}{6 \sqrt{n}} \phi^{(2)}(\xi)-\frac{\lambda_{4}}{24 n} \phi^{(3)}(\xi)-\frac{\lambda_{3}^{2}}{72 n} \phi^{(5)}(\xi), \quad \text { for } \delta>0  \tag{2.4}\\
& \alpha^{\prime}=\alpha_{N}-\alpha_{C} \tag{2.5}
\end{align*}
$$

Where $\xi=(k-\delta \sqrt{n})$
and $\alpha_{C}=\frac{\left[3 \lambda_{4} \phi^{(3)}(k)+\lambda_{3}^{2} \phi^{(5)}(k)\right]}{36 n}$
is the non-normality correction for $\alpha$.

## 3. Optimum Value of Sample Size $n$ and Sampling Interval $h$

One can determine the optimum value of sample size $n_{0}$ and sampling interval $h_{0}$ either by maximizing the gain function $I$
or by minimizing the cost function $L$ with respect to $n$ and $h$. After solving for minimizing the cost function L, we find the
One can determine the optimum value of sample size $n_{0}$ and sampling interval $h_{0}$ either by maximizing the gain function $I$
or by minimizing the cost function $L$ with respect to $n$ and $h$. After solving for minimizing the cost function L, we find the following two equations

$$
\begin{equation*}
h=\left\{\frac{\alpha^{\prime} T+b+c n}{\eta M\left(\frac{1}{P^{\prime}}-\frac{1}{2}\right)}\right\}^{\frac{1}{2}} \tag{3.1}
\end{equation*}
$$

$-\frac{\alpha^{\prime} T+b+c n}{P^{\prime 2}\left(\frac{1}{P^{\prime}}-\frac{1}{2}\right)} \cdot \frac{\partial P^{\prime}}{\partial n}-\eta \alpha^{\prime} T+\frac{T \alpha_{C}}{n}\left\{\frac{\eta M\left(\frac{1}{P^{\prime}}-\frac{1}{2}\right)}{\alpha^{\prime} T+b+c n}\right\}^{\frac{1}{2}}+c=0$.

The value of $n$ for which the equation (3.2) satisfy yield us the required optimum value of the sample size $n_{0}$. Substituting this value of $n$ in equation (3.1), we find the optimum value of the sampling interval $h_{0}$.

## 4. Description for Optimum Value of Sample Size $n$ and Sampling Interval $h$ under Measurement Error

Assuming that the true measurement $x$ and the random error of measurement $e$ are additive, then
$X=x+e$.
The mean and standard deviation of the observed measurement $X$ can be written as
$E(X)=\mu, \quad V(X)=\sigma_{X}^{2} . \quad$ (say)
where $\mu$ is the mean of $x$ and $e \sim N\left(0, \sigma_{e}^{2}\right)$,
The correlation coefficient $\rho$ between the true and observed measurement is given by

$$
\begin{equation*}
\rho=\frac{r}{\sqrt{1+r^{2}}} \tag{4.2}
\end{equation*}
$$

Where $r=\frac{\sigma_{p}}{\sigma_{e}}$.
Now since $x$ and $e$ are independent, the $r^{\text {th }}$ cumulant of X is equal to the sum of the $r^{\text {th }}$ cumulants of $x$ and $e$. Further, since $e \sim N\left(0, \sigma_{e}^{2}\right)$, all the cumulants of $e$ are zero except the second one which is $\sigma_{e}^{2}$. Thus, if we denote by $k_{r}$ and $l_{r}$ the $r^{\text {th }}$ cumulants of $X$ and $x$ respectively, we have $k_{r}=l_{r}, \quad r \neq 2$

Let $v_{r}$ and $\lambda_{r}(r \neq 2)$ be the rth standardized cumulants of $X$ and $x$ respectively, then
$v_{r}=\frac{k_{r}}{\left(k_{r}\right)^{r / 2}}=\frac{l_{r}}{\left(\sigma_{X}\right)^{r}}=\frac{l_{r}}{\left(\sigma_{p} / \rho\right)^{r}}$
or $\quad v_{r}=\rho^{r} \lambda_{r}$.

So the probability density function for non-normal population under non-normality and measurement error will be

$$
\begin{aligned}
& P_{\varepsilon}^{\prime}=1-\Phi\left(\xi_{\varepsilon}\right)+\frac{\rho^{3} \lambda_{3}}{6 \sqrt{n}} \phi^{(2)}\left(\xi_{\varepsilon}\right)-\frac{\rho^{4} \lambda_{4}}{24 n} \phi^{(3)}\left(\xi_{\varepsilon}\right) \\
&-\frac{\rho^{6} \lambda_{3}^{2}}{72 n} \phi^{(5)}\left(\xi_{\varepsilon}\right), \quad \text { for } \delta>0
\end{aligned}
$$

$\alpha_{e}^{\prime}=\alpha_{N e}-\alpha_{C e}$

Where $\quad \xi_{e}=\rho(k-\delta \sqrt{n})$,
$\alpha_{N e}=2 \Phi(-\rho k)$,
$\alpha_{C e}=\frac{\left[3 \rho^{4} \lambda_{4} \phi^{(3)}(k)+\rho^{6} \lambda_{3}^{2} \phi^{(5)}(k)\right]}{36 n}$.
In presence of non-normality and measurement error, the equation (3.1) and (3.2) will reduce in following form

$$
\begin{equation*}
h_{e 0}=h=\left\{\frac{\alpha_{e}^{\prime} T+b+c n}{\eta M\left(\frac{1}{P_{e}^{\prime}}-\frac{1}{2}\right)}\right\}^{\frac{1}{2}} \tag{4.3}
\end{equation*}
$$

and

Again the value of $n$ for which the equation (4.5) satisfy give us the required optimum value of the sample size $n_{e 0}$, and putting this value in equation (4.4), we find the optimum
value of the sampling interval $h_{e 0}$ under non-normality and measurement error.

## 5. Numerical Illustration

For the purpose of numerical illustration, we take
$\lambda_{3}=-0.5,0,0.5, \quad \lambda_{4}=-0.5,0,1.0,2.0, \quad k=2.0,3.0, \delta=0.5,1.0,2.0$,
$\eta=0.01, \quad M=100, \quad W=25, \quad T=50, \quad C=0.05, \quad D=2, \quad b=0.5, \quad c=0.1$,
and $r=\infty, 2,6$ and determine the optimum value of sample size and sampling interval. The values of $n_{0}$ and $h_{0}$ are presented in the Table-1,

Table 1: Values of the optimum sample size $n$ and sampling interval $h$ under measurement error for $r=\infty$

| $\delta$ | $\begin{gathered} \boldsymbol{\lambda}_{\mathbf{3}} \rightarrow \\ \boldsymbol{\lambda}_{4 \downarrow} \end{gathered}$ | K=3 |  |  |  |  |  | K=2 |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | -0.5 |  | 0.0 |  | 0.5 |  | -0.5 |  | 0.0 |  | 0.5 |  |
|  |  | n | h | n | h | n | h | n | h | n | h | n | h |
| 0.5 | -0.5 | 66 | 3.2781 | 67 | 3.3254 | 68 | 3.3652 | 41 | 3.2800 | 42 | 3.3288 | 43 | 3.3897 |
|  | 0.0 | 66 | 3.2990 | 67 | 3.3392 | 68 | 3.3782 | 42 | 3.3334 | 42 | 3.3568 | 43 | 3.3927 |
|  | 1.0 | 67 | 3.3451 | 68 | 3.3894 | 68 | 3.4034 | 43 | 3.4173 | 44 | 3.4325 | 44 | 3.4440 |
|  | 2.0 | 67 | 3.3576 | 68 | 3.4051 | 69 | 3.4483 | 44 | 3.4644 | 45 | 3.5057 | 45 | 3.5146 |
| 1.0 | -0.5 | 17 | 1.8675 | 17 | 1.9237 | 18 | 1.9413 | 29 | 2.6164 | 29 | 2.6288 | 29 | 2.6395 |
|  | 0.0 | 18 | 1.9911 | 18 | 2.0026 | 19 | 2.0605 | 31 | 2.7513 | 31 | 2.7709 | 31 | 2.7706 |
|  | 1.0 | 21 | 2.2002 | 21 | 2.2088 | 21 | 2.2198 | 34 | 2.9405 | 34 | 2.9574 | 34 | 2.9575 |
|  | 2.0 | 23 | 2.3422 | 23 | 2.3498 | 23 | 2.3590 | 37 | 3.1234 | 37 | 3.1076 | 37 | 3.1104 |
| 2.0 | -0.5 | 3 | 1.0032 |  | 1.1150 | 4 | 1.1563 | 24 | 2.2733 | 25 | 2.3256 | 25 | 2.3526 |
|  | 0.0 | 5 | 1.4340 | 5 | 1.4336 | 5 | 1.4543 | 26 | 2.4460 | 27 | 2.4898 | 27 | 2.4569 |
|  | 1.0 | 13 | 1.9632 | 12 | 1.9192 | 12 | 1.9317 | 30 | 2.7167 | 34 | 2.9294 | 33 | 2.8916 |
|  | 2.0 | 17 | 2.1800 |  | 2.1845 | 17 | 2.1931 | 34 | 2.9623 | 37 | 3.1026 | 37 | 3.0967 |

Table 2: Values of the optimum sample size $n$ and sampling interval $h$ under measurement error for $\mathbf{r}=2$

| $\delta$ | $\begin{gathered} \boldsymbol{\lambda}_{\mathbf{3}} \rightarrow \\ \boldsymbol{\lambda}_{4 \downarrow} \end{gathered}$ | K=3 |  |  |  |  |  | K=2 |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | -0.5 |  | 0.0 |  | 0.5 |  | -0.5 |  | 0.0 |  | 0.5 |  |
|  |  | n | h | n | h | n | h | n | h | n | h | n | h |
| 0.5 | -0.5 | 95 | 4.3423 | 94 | 4.3129 | 95 | 4.3487 | 85 | 4.9819 | 85 | 4.9864 | 86 | 5.0030 |
|  | 0.0 | 95 | 4.3548 |  | 4.3442 | 96 | 4.3796 | 86 | 4.9951 | 86 | 5.0154 | 87 | 5.0323 |
|  | 1.0 | 96 | 4.3709 |  | 4.3600 | 97 | 4.4105 | 86 | 5.0141 | 87 | 5.0423 | 88 | 5.0671 |
|  | 2.0 | 97 | 4.4017 |  | 4.3762 | 98 | 4.4409 | 87 | 5.0345 | 88 | 5.0665 | 89 | 5.0803 |
| 1.0 | -0.5 | 112 | 4.8096 | 112 | 4.8137 | 113 | 4.8428 | 90 | 5.0842 | 91 | 5.1193 | 92 | 5.1429 |
|  | 0.0 | 113 | 4.8347 | 114 | 4.8633 | 114 | 4.8675 | 90 | 5.0992 | 92 | 5.1410 | 94 | 5.1854 |
|  | 1.0 | 114 | 4.8597 | 114 | 4.8756 | 115 | 4.8921 | 91 | 5.1166 | 93 | 5.1630 | 95 | 5.2068 |
|  | 2.0 | 116 | 4.9085 | 116 | 4.9123 | 116 | 4.9164 | 92 | 5.1389 | 96 | 5.2262 | 96 | 5.2281 |
| 2.0 | -0.5 | 130 | 5.2218 | 131 | 5.2455 | 131 | 5.2484 | 110 | 5.4975 | 112 | 5.5369 | 112 | 5.5376 |
|  | 0.0 | 131 | 5.2430 | 132 | 5.2665 | 132 | 5.2693 | 112 | 5.5354 | 113 | 5.5558 | 112 | 5.5470 |
|  | 1.0 | 132 | 5.2642 | 132 | 5.2770 | 134 | 5.3106 | 115 | 5.5916 | 114 | 5.5748 | 113 | 5.5570 |
|  | 2.0 | 132 | 5.2747 | 134 | 5.3083 | 135 | 5.3312 | 116 | 5.6105 | 116 | 5.6121 | 117 | 5.6308 |

Volume 11 Issue 11, November 2022

Table 3 : Values of the optimum sample size $\mathbf{n}$ and sampling interval $h$ under measurement error for $r=6$

| $\delta$ | $\begin{gathered} \boldsymbol{\lambda}_{3} \rightarrow \\ \boldsymbol{\lambda}_{4 \downarrow} \end{gathered}$ | K=3 |  |  |  |  |  | K=2 |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | -0.5 |  | 0.0 |  | 0.5 |  | -0.5 |  | 0.0 |  | 0.5 |  |
|  |  | n | h | n | h | n | h | n | h | n | h | n | h |
| 0.5 | -0.5 | 87 | 4.1063 |  | 4.1453 | 88 | 4.1518 | 66 | 4.2658 | 66 | 4.2734 | 67 | 4.3059 |
|  | 0.0 | 87 | 4.1230 |  | 4.1783 | 90 | 4.2169 | 67 | 4.2953 | 68 | 4.3310 | 68 | 4.3347 |
|  | 1.0 | 88 | 4.1406 |  | 4.1949 | 91 | 4.2492 | 68 | 4.3249 | 68 | 4.3458 | 69 | 4.3637 |
|  | 2.0 |  | 4.1739 |  | 4.2120 | 92 | 4.2810 | 68 | 4.3398 | 69 | 4.3611 | 69 | 4.3783 |
| 1.0 | -0.5 | 104 | 4.6071 | 104 | 4.6125 | 105 | 4.6440 | 79 | 4.6105 | 80 | 4.6396 | 80 | 4.6418 |
|  | 0.0 | 105 | 4.6333 | 105 | 4.6386 | 106 | 4.6697 | 81 | 4.6590 | 81 | 4.6638 | 82 | 4.6893 |
|  | 1.0 | 105 | 4.6464 | 106 | 4.6646 | 107 | 4.6953 | 82 | 4.6834 | 82 | 4.6881 | 83 | 4.7133 |
|  | 2.0 | 106 | 4.6599 |  | 4.7153 | 109 | 4.7451 | 84 | 4.7308 | 84 | 4.7351 | 85 | 4.7597 |
| 2.0 | -0.5 | 119 | 4.9685 | 120 | 4.9943 | 120 | 4.9981 | 91 | 4.8850 | 91 | 4.8883 | 91 | 4.8894 |
|  | 0.0 | 119 | 4.9796 | 121 | 5.0164 | 122 | 5.0416 | 92 | 4.9070 | 92 | 4.9101 | 93 | 4.9324 |
|  | 1.0 | 120 | 4.9912 | 121 | 5.0273 | 123 | 5.0633 | 93 | 4.9292 | 94 | 4.9533 | 94 | 4.9543 |
|  | 2.0 | 121 | 5.0135 | 123 | 5.0602 | 124 | 5.0848 |  | 4.9511 | 95 | 4.9750 | 95 | 4.9760 |

when $r=\infty$ (error free), it is evident from the table that for given $k$ and $\delta$ the value of $n_{0}$ and $h_{0}$ increases with the increase in the value of $\lambda_{4}$ and practically remain the same with the increase in the value of $\lambda_{3}$. For large values of $\delta$ the effect of kurtosis seems to be more marked than that of skewness. As the size of error increases the value of $n_{0}$ and $h_{0}$ is seriously affected.

## 6. Conclusion

It may be inferred that measurement errors affects considerably the optimum value of the sample size and optimum sampling interval. It is necessary to point out that the measurement errors and non-normality of the population should be taken in to account while designing a control chart as the optimum values of the control chart parameters are affected by the measurement errors and non-normality of the population.

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