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INFLUENCE OF SPECIAL CAUSES ON STOCHASTIC PROCESS ADJUSTMENT†

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ABSTRACT

Process adjustment is a complimentary tool to process monitoring in process control. Although original intention of process adjustment is not identifying a special cause, detection and elimination of special causes may lead to significant process improvement. In this paper, we examine the impact of special causes on process adjustment. The bias in the adjusted output process is derived for each type of special causes, and average run length (ARL) of the Shewhart chart applied to the adjusted output is computed for each special cause types. Numerical results are illustrated for the ARL of the Shewhart chart, thereupon seriousness of special causes on process adjustment is evaluated for each type of special causes.

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1. INTRODUCTION

Process monitoring and process adjustment are two complementary approaches to process control. These two procedures share a common objective: reduction of variability (Box *et al.*, 1994; Montgomery, 2001). Process monitoring, which is part of statistical process control (SPC), focuses on identifying special causes and then eliminating sources of the causes, from which process variability is reduced and process performance is improved. Meanwhile, process adjustment, also called engineering process control (EPC), directs on maintaining a process output close to a target value by manipulating another controllable variable. Uncontrollable phenomena such as variations in ambient temperature and humidity or causes

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currently unknown may lead to a tendency for the process to wander off target. Such sources of variability may be unavoidable and cannot be eliminated by process monitoring. Process adjustment can be applied to minimize process variability for such circumstances.

When special causes such as mistakes by the operator or sudden changes in environmental conditions occur, process adjustment may not properly function to compensate the effects of intervention. It thus may result in off-target bias and increased variability in output process possibly for long periods. Process adjustment does not initially intend to identify a special cause that may influence the process, yet detection and elimination of special causes can lead to significant process improvement. In an effort to provide an improved performance, approaches combining SPC and EPC are proposed, in which a control rule is applied to process adjustment and a control chart is applied to the adjusted output for process monitoring. Vander Wiel *et al.* (1992) proposed a minimum mean square error (MMSE) control algorithm and a scheme for monitoring the output by the CUSUM chart, namely the ASPC. Montgomery *et al.* (1994) investigated two types of special causes, a sustained shift and a linear trend, and demonstrated that the combined procedure outperforms the EPC procedure alone (also, see MacGregor, 1987; MacGregor and Harris, 1990; Box and Kramer, 1992; Montgomery *et al.*, 1994; Capilla *et al.*, 1999; Montgomery, 2001; Chen and Elsayed, 2002). In addition, process monitoring for auto-correlated series has noticeable similarity with process adjustment. Performance of various monitoring charts has been investigated for special cause of level shift (Alwan and Roberts, 1988; Wardell *et al.*, 1994; Vander Wiel, 1996; Atienza *et al.*, 1998).

In this paper, we consider a responsive feedback control system for which all the effect of a change in the controllable variable will be realized on the output process in one period. The underlying process is assumed to follow IMA(1,1) process and MMSE forecast is employed in manipulation of controllable input variable. It is well known that the output process adjusted by the optimal control rule, *i.e.*, the residual series of process adjustment, is an independent and identically distributed (IID) process and thus has minimum variability (Box *et al.*, 1994). However, when a special cause occurs in the underlying process, it may produce bias in the adjusted output series. Yet, bias decrease over time, because the effect of the cause become adjusted to some degree in the process of manipulating input variable. Though for process monitoring, level shift is the special cause type most concerned, special causes of different types may lead to different degrees of seriousness in process adjustment. Thus, understanding the effects of special causes of different types on process adjustment may provide important information for improving process performance. We first introduce a *general framework* for modelling the special cause problems in process adjustment. Two types of special causes, additive outlier (AO) and level shift (LS), are considered. The effect of the causes on adjusted output process is derived for the case that the MMSE (optimal) control rule is applied to the underlying process contaminated by the causes. Based on derived results, the ARL's of Shewhart chart are computed for various parameter values of underlying processes model, and impact of the cause on process adjustment is evaluated for each type of special cause. Numerical results are illustrated for the run-length distribution and the ARL of the Shewhart chart, showing that AO type special cause can lead to more serious bias than LS type in the adjusted output series.

2. IMPACTS OF SPECIAL CAUSES ON OUTPUT PROCESS

We consider a *responsive feedback control system* for which all the effect of a change in a controllable variable will be realized on the output in one period,

$$U_t = Y_t + Z_t, \tag{2.1}$$

where U_t is the amount of deviation from the target when control action is applied *via* X_t, Z_t is the amount of deviation from target in the system output when no control action is applied, and $Y_t = gX_{t-1}$ is the amount of compensation on the output at time t when controllable input variable is set as X_{t-1} at time $t-1$, where g is the steady state gain (Box *et al.*, 1994). In the system (2.1), Z_t, X_t, and U_t are called *underlying process* (also called unadjusted output), *input* variable, and *adjusted output*, respectively.

2.1. The minimum mean square error control rule

In this paper, we assume that the underlying process Z_t can be represented by IMA(1,1) model

$$Z_t = Z_{t-1} + a_t - \theta a_{t-1}, \tag{2.2}$$

where a_t is a sequence of white noise with mean zero and constant variance σ_a^2 and $|\theta| < 1$. It is also assumed that the series Z_t starts at a fixed time point t_0 with fixed initial values and initial innovations. This process (2.2) is of particular importance in process adjustment. If the series Z_t are left unadjusted, there is no guarantee that they will return to the target value in a finite time. In fact, many processes generated under the uncontrollable phenomena demonstrate such characteristic, and it can be approximately represented by IMA(1,1) model (Vander Wiel *et al.*, 1992; Montgomery *et al.*, 1994; Box and Luceño, 1997; Montgomery, 2001; Capilla *et al.*, 1999; Del Castillo, 2002). In process adjustment, the model and true parameters of Z_t are *known* in general, or they can be identified and estimated by any consistent estimators in the implementing stage of process control.

It is well known that a control equation,

$$X_{t-1} = -\frac{Z_{t-1}(1)}{g}, \tag{2.3}$$

where $Z_{t-1}(1) = \lambda \sum_{j=1}^{\infty} \theta^{j-1} Z_{t-j}$ is exponentially weighted moving average (EWMA) of Z_t forecasted at time $t-1$ and $\lambda = 1-\theta$, is the MMSE control (optimal) rule that minimizes the adjusted output variability. That is, the adjusted output is one-step-ahead MMSE forecast error that is white noise as follows:

$$U_t = e_{t-1}(1) = a_t. \tag{2.4}$$

In practice, Z_t is usually un-observable. Then, the input variable can be manipulated in terms of past adjusted output series by $X_{t-1} = -\lambda \sum_{j=1}^{\infty} U_{t-j}/g$ where a different expression of MMSE forecast, $Z_{t-1}(1) = \lambda \sum_{j=1}^{\infty} a_{t-j}$, and (2.4) are applied (Box *et al.*, 1994).

2.2. Impact of a special cause

Process adjustment employs a system of statistical forecasting, and thus special causes generally produce carry-over-effects on process control. Even though MMSE control rule given in (2.3) minimizes the variation of output process, special causes occurred in a underlying process may produce off-target bias and additional variability in adjusted outputs possibly for long periods. For process monitoring, level shift is the special cause type most concerned and AO type cause is less crucial since though it is not detected it may not significantly deteriorate overall performance of the procedure. Meanwhile, special causes of both types may lead to crucial effects on process adjustment in that once occurred, each of them can produce significant biases possibly for long periods, because of the carry-over-effects in the process adjustment. Therefore, understanding the effects of special cause of each type on process adjustment may provide important information for improving process performance. If a special cause occurs at time

T, the underlying process is contaminated by the cause, denoted by N_t, and can be represented by

$$N_t = Z_t + \omega\xi(B)I_t(T), \tag{2.5}$$

where T, ω, and $\xi(B) = 1 + \xi_1 B + \xi_2 B^2 + \cdots$ are the occurrence time, the *impact parameter*, and the type of the special cause, respectively. In (2.5), B is the backshift operator, which is defined by $BY_t = Y_{t-1}$, and $I_t(T) = 1$ if $t = T$ and 0 otherwise signifies the pulse indicator at time T.

If the special cause has not been detected and thus a contaminated series N_t, instead of Z_t, is applied to EWMA forecast given in (2.3), the forecast at time $t-1$, denoted by $\widehat{Z}_{t-1}(1)$, can be expressed in terms of $Z_{t-1}(1)$ as

$$\widehat{Z}_{t-1}(1) = Z_{t-1}(1) + \omega \sum_{i=1}^{t-T} \lambda\theta^{i-1}\xi_{t-T-i}. \tag{2.6}$$

The identity $\xi(B)I_t(T) = I_t(T) + \xi_1 I_{t-1}(T) + \xi_2 I_{t-2}(T) + \cdots = \xi_{t-T}$ is used in derivation of (2.6). From now on, the '$\wedge$' above any character will signify the use of the contaminated series N in computation of the statistic. For such circumstance, from (2.3) and (2.6), input variable will be manipulated by $\widehat{X}_{t-1} = -\widehat{Z}_{t-1}(1)/g$, and the impact of the special cause on the input variable can be written as

$$\widehat{X}_{t-1} = X_{t-1} - \omega \sum_{i=1}^{t-T} \frac{\lambda\theta^{i-1}\xi_{t-T-i}}{g}. \tag{2.7}$$

The adjusted output affected by the cause, denoted by $\widehat{U}_t$, can be written as:

$$\begin{aligned} \widehat{U}_t &= N_t + g\widehat{X}_{t-1} \\ &= e_{t-1}(1) + \omega\left\{\xi_{t-T} - \sum_{i=1}^{t-T} \lambda\theta^{i-1}\xi_{t-T-i}\right\}. \end{aligned} \tag{2.8}$$

Therefore, the mean level of the output shifts to the second term of (2.8).

We now consider special causes whose impacts on the underlying process show specific patterns. Adopting outlying patterns in time series, the type of AO can be expressed as $\xi(B) = 1$ and LS type as $\xi(B) = 1/(1-B)$ (see, Tsay, 1986 and 1988; Chen and Liu, 1993; Pankratz, 1991). From the second terms in (2.7) and (2.8), the impact of special causes on the input variable and the adjusted output series can be explicitly expressed as $-\omega\lambda\theta^{t-T-1}/g$ and $-\omega\lambda\theta^{t-T-1}$ for AO and $-\omega(1-\theta^{t-T})/g$ and $\omega\theta^{t-T}$ for LS, respectively, as summarized in Table 2.1. We note that the bias in the adjusted output series is ω at $t = T$ for both types, but it decreases as time passes from T. Bias in the adjusted output due to a special cause can be interpreted as the mean shift at each time point. We thus note that both of the special causes produce decreasing mean shifts in the adjusted output process, though mean shifts vanish eventually. Therefore, we can predict that Shewhart chart applied to adjusted output series for LS type special cause may not perform as well as what we expect for IID series. In this paper, we examined the effects of special causes of AO and LS type for IMA(1,1) underlying process, but it can be easily extended to any type of special cause and model of underlying process. For example, innovational outlier (IO) type and consecutive AO type may be considered by expressing $\xi(B)$ in (2.5) as $\xi(B) = \psi(B)$ and $\omega\xi(B) = \sum_{j=0}^{m-1} \omega_j I_t(T+j)$, where $\psi(B)$ is the infinite MA operator in the expression of the underlying process $Z_t = \psi(B)a_t$. The model of underlying process can be extended to ARIMA(p,d,q) model, and the effects of special causes on U_t can be derived as done in equations (2.6) through (2.8).

TABLE 2.1 *Bias at time ($t > T$) in the input and output series*

Type	$\xi(B)$	*Bias*	
		Input Process	*Output Process*
AO	$\xi(B) = 1$	$-\omega\lambda\theta^{t-T-1}/g$	$-\omega\lambda\theta^{t-T-1}$
LS	$\xi(B) = 1/(1-B)$	$-\omega(1-\theta^{t-T})/g$	$\omega\theta^{t-T}$

3. COMPUTATION OF ARL

We consider the average run length, which is defined as the expected number of samples taken before the process exceeds the control limits, as a performance measure for control chart. It is well known that Shewhart chart is very effective in detecting moderate to large level shifts for IID process, whereas CUSUM and EWMA charts outperform Shewhart chart when the size of level shift is small (see, Crowder, 1987 and 1989; Lucas and Saccucci, 1990; Woodall and Adams, 1993). In this section, the ARL of the combined scheme will be compared to that of SPC scheme for IID process. The ARL when the process mean shifts off-target, denoted by ARL_1, will be evaluated, subject to a specified ARL of 'on-target' (ARL_0). For IID processes, the ARL_0 of Shewhart control chart can be computed as

$$\text{ARL}_0 = \frac{1}{P_0}$$

where P_0 is the probability that a sample exceeds specified control limits. In general, Shewhart chart employs three-sigma limits, thereupon P_0 is 0.0027 and ARL_0 is 370, approximately. In practice, we are mainly interested in studying the ARL for the specified control limits and special causes with a impact parameter ω. The ARL_1 of the combined scheme is different from that of IID process in that the bias due to special causes, *i.e.*, mean shift, decreases over time. The distribution of run-length can be determined for each run length. It is to be noted that the distributions are not identical, being different from IID cases. Using the distributions of run-length, the ARL_1 can be computed for the specified control limits and level shift occurred in the underlying process.

We first consider the run-length distribution of the Shewhart chart when a LS type special cause occurs. The case of AO type cause can be done in this manner. The adjusted output at $t = T + i - 1$, which is the time point after $i - 1$ periods passed the occurrence time, is represented as

$$\widehat{U}_{T+i-1} = a_{T+i-1} + \omega\theta^{i-1}$$

for $i = 1, 2, \ldots$, in which the mean of the adjusted output is $\omega\theta^{i-1}$. Then, the probability that the output at that time point exceeds the control limits, $P(|\widehat{U}_t| > 3\sigma_a)$, denoted as P_t, can be represented as

$$P_i = 1 - F(3\sigma_a - \omega\theta^{i-1}) + F(-3\sigma_a - \omega\theta^{i-1}), \qquad i = 1, 2, \ldots, \tag{3.1}$$

where $F(\cdot)$ is the standard normal cumulative distribution function. If we define R to be a discrete random variable representing the run length of the Shewhart chart, then the distribution of R is defined by the probabilities in (3.1). Its probability mass function (*pmf*) is given by

$$P(R = r) = P_r \prod_{i=0}^{r-1} (1 - P_i), \qquad r = 1, 2, \ldots, \tag{3.2}$$

where $P_0 = 0$. If there is no level shift, P_t is constant in t and (3.2) thus follows the geometric distribution, which is the run-length distribution of the standard Shewhart chart. Given the *pmf* in (3.2), any moments can be computed.

As an example, Figure 3.1 shows the *pmf*s of the run-length of the Shewhart chart for the adjusted output process when the underlying process follows

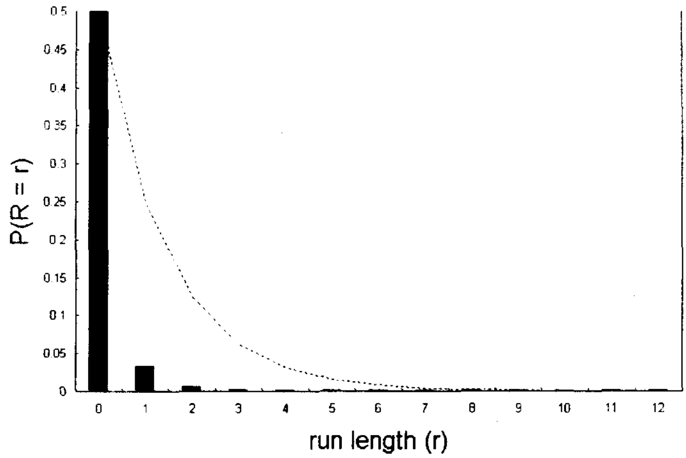

FIGURE 3.1 *A portion of the pmf of the run-length of the Shewhart chart for the IMA(1,1) process with $\theta = 0.5$ when $\omega = 3\sigma_a$; for adjusted output (solid line), for IID process (dash line)*

IMA(1,1) with $\theta = 0.5$ and for the IID process, for the first 13 run lengths. (For illustration purposes we have truncated the *pmf* at run length 13 because probabilities are stabilized from run length 13.) It shows the run-length distribution for a level shift of $\omega = 3\sigma_a$, measured in the standard deviation of a_t. We note that the probability of obtaining a signal at a length of 1 is relatively large, but the probability decreases significantly as run-length increases. We also observe that having a level shift in the underlying process is reflected in course of process adjustment. In Figure 3.1, it also can be observed that the probability of giving a signal for IID process is much larger than that for adjusted output at several short run lengths. Therefore, we can predict that the ARL for the adjusted output process will be larger than that for the IID process. In Table 2.1, we can expect that the AO type cause will show similar result as LS type, being equivalent to the $\theta = 0.5$ case.

The ARL_1 can be computed by defining equation of ARL,

$$\text{ARL} = \sum_{r=1}^{\infty} r P_r \prod_{i=1}^{r-1} (1 - P_i). \tag{3.3}$$

The defining equation of ARL consists of infinite sums, and thus the approach proposed by Wardell *et al.* (1994) is considered to approximate ARL. Although we primarily consider the LS type cause, but the method can be applied to AO type cause. The mean at time t in adjusted output series is $\omega\theta^{t-T}$ and it converges to 0 as t increases. Therefore, we will have $P_{t+1} \approx P_t$ - namely from some value of t, when $\omega\theta^{t-T}$ term becomes sufficiently small. By determining τ as the first integer satisfying $|\omega\theta^{t-T}| < \varepsilon$ where ε is a pre-determined real number which is close to zero, the ARL can be computed from (3.3). Probabilities after $\tau - 1$ time periods after the occurrence of the LS are set equal to a fixed constant, P_τ.

Now, (3.2) can be simplified when r is greater than or equal to τ. The *pmf* of run-length can be written as

$$P(R = r) = P_r \times (1 - P_\tau)^{r-\tau} \prod_{i=0}^{\tau-1} (1 - P_i), \qquad r = \tau, \tau + 1, \ldots \tag{3.4}$$

If we use the cutoff value τ, it is easy to show that the ARL of Shewhart chart can be approximated by

$$\text{ARL} = \sum_{r=1}^{\tau} r P_r \prod_{i=1}^{r-1} (1 - P_i) + \Big(\frac{1}{P_\tau} + \tau\Big) \prod_{j=0}^{\tau} (1 - P_j), \tag{3.5}$$

where P_j is given in (3.1).

4. AN ILLUSTRATIVE NUMERICAL EXAMPLE

In order to evaluate the performance of Shewhart control chart for the adjusted output process, several ARL's are computed for different values of parameter θ in IMA(1,1) process and magnitudes of impact parameter. In this study, $\theta = \pm 0.2, \pm 0.5$ and ± 0.8 are considered as representative parameter values. The magnitudes of impact parameter ω, *i.e.*, the amount of level shits, considered in this example are from 0 to 5 multiple of the standard deviation of a_t, σ_a, with $0.5\sigma_a$ intervals. Without loss of generality, $\sigma_a = 1.0$ is employed in this study. In addition, the ARL's of Shewhart chart for IID process are computed to compare to the ARL's for the adjusted output process.

Three-sigma control limits is applied to Shewhart control chart, resulting in ARL_0 of 370 for IID process. Since adjusted output process is a sequence of white noise, the ARL_0 for the combined procedure is also approximately 370. To determine the cutoff value τ, $\varepsilon = 0.001$ is applied to have reasonably accurate approximation of ARL. For example, a smallest integer exceeding $\log(0.001/\omega)/\log\theta$ is selected as τ for each combination of ω and θ to determine τ as the first integer satisfying $|\omega\theta^{t-T}| < \varepsilon$ for LS type cause. Based on the determined τ, the ARL is computed from equations (3.4) and (3.5). The ARL's of Shewhart chart for adjusted output process and IID process are summarized in Table 4.1 and 4.2 for

LS and AO type special causes, respectively.

TABLE 4.1 *The ARL of the Shewhart chart for LS type special cause; the ARL of a negative parameter is the same as that of the corresponding positive parameter*

θ \ ω	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
0.2	370.4	369.0	362.8	346.2	311.9	256.1	185.1	114.3	59.1	25.4	9.3
0.5	370.4	368.6	361.2	342.4	304.9	245.6	172.2	101.7	49.4	19.6	6.6
0.8	370.4	366.7	352.9	320.9	263.1	182.9	101.0	41.8	12.7	3.3	1.3
IID	370.4	155.2	43.9	15.0	6.3	3.2	2.0	1.4	1.2	1.1	1.0

TABLE 4.2 *The ARL of the Shewhart chart for AO type special cause*

θ \ ω	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.5	5.0
−0.8	370.4	355.4	283.9	139.9	29.4	3.2	1.5	1.3	1.2	1.1	1.0
−0.5	370.4	364.5	335.6	260.2	145.9	51.3	10.8	2.2	1.2	1.1	1.0
−0.2	370.4	366.9	350.6	307.2	227.2	129.0	51.8	14.3	3.2	1.3	1.0
0.2	370.4	368.1	358.8	334.9	287.9	216.7	135.4	67.2	25.7	7.8	2.3
0.5	370.4	368.6	361.2	342.4	304.9	245.6	172.2	101.7	49.4	19.6	6.6
0.8	370.4	368.8	362.4	345.5	310.7	254.6	183.5	112.9	58.1	24.8	9.0

Significant mean shifts in the adjusted output series lead to smaller ARL's, and thus we may interpret the ARL values as overall impact of a special cause on process adjustment. The following observations are obtained from the ARL's, of Shewhart control charts in Table 4.1 and 4.2:

1. For LS type cause, the ARL's are symmetric in θ and a decreasing function of $|\theta|$ for each magnitude of level shift. Since the mean shift in $\widehat{U}_t$ is $\omega\theta^{t-T}$, larger θ leads to larger mean level in $\widehat{U}_t$. Therefore, the impact of LS on process adjustment become greater as $|\theta|$ increases. Meanwhile, when AO type special cause occurs, the ARL is an increasing function of θ. It is important to note that two types produce same ARL values at $\theta = 0.5$. However, the impact of AO type on process adjustment is greater than that of LS type for $\theta < 0.5$, whereas LS type generate more serious impact

for $\theta > 0.5$. We can also confirm these findings in Table 2.1.

2. The ARL is a decreasing function of ω. While ARL is large, the probability of giving a signal at run length of small number is generally much greater than the probability associated with run length of large number, as shown in Figure 3.1. We are interested in detecting smaller level shift for process monitoring. On the other hand, the impact of a special cause on the output series is entertained and thus reduced in process adjustment. Therefore, early detection of the cause is crucial for process improvement. That is, ARL's at larger ω are more important than those of smaller ω cases.

3. Compared to the ARL of Shewhart chart for IID process, the ARL for LS type is much larger. Such results arise because the impacts of special causes becomes adjusted to some degree in the process of manipulating input variable. As a result, mean shift in $\widehat{U}_t$ decreases as $\omega\theta^{t-T}$, resulting in relatively larger ARL values. Thus, the efficiency of Shewhart applied to the combined approach can be much lower than the efficiency of IID case. The AO type cause shows similar results for positive model parameters, whereas it shows notable effectiveness for negative parameter values.

In summary, the ARL's of Shewhart chart applied to combined approach are obtained. Yet, effectiveness of the chart may be unrealiable in certain circumstances especially in case of smaller impact parameter values. It is also notable that, compared to LS type cause, the AO type can yield greater influences on process adjustment for certain parameter values of the underlying process model.

5. SUMMARY AND CONCLUSION

Process adjustment may be applied when a process output can be maintained close to a target value by manipulation of another controllable variable. In this paper, we consider a responsive control system, in which the underlying process follows IMA(1,1) process and MMSE control rule is applied. By employing a model for the underlying process that is contaminated by a special cause, the effect of the cause on process adjustment is derived, namely on manipulation of controllable (input) variable and on adjusted output. The ARL's of Shewhart control chart applied to the adjusted output process are computed based on the results.

As an illustrative numerical example, two specified type of special causes, LS and AO, are considered. From the standpoint of ARL as a performance measure, the impact of the cause of LS type on process adjustment can be severe as $|\theta|$ becomes close to 1, whereas the impact of AO type becomes greater as θ decreases. Two types produce same ARL values at $\theta = 0.5$. However, the impact of AO type on process adjustment is greater than that of LS type when $\theta < 0.5$, and LS type produces greater impact when $\theta > 0.5$. The effectiveness of Shewhart chart applied to process adjustment is in doubt, particularly when the parameter value of the underlying process is not close to 1 for LS type and is close to 1 for AO type. It is also shown that performance of Shewhart chart for the adjusted output process is considerably lower than performance for IID process. More efficient schemes may be employed to detect special causes in process adjustment.

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