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ORIGINAL ARTICLE

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An approach to controlling two dependent process steps with autocorrelated observations

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Abstract The observations from the process output are always assumed independent when using a control chart to monitor a process. However, for many processes the process observations are autocorrelated. This autocorrelation can have a significant effect on the performance of the control chart. This paper considers the problem of monitoring the mean of a quality characteristic X on the first process step and the mean of a quality characteristic Y on the second process step, in which the observations X can be modeled as an AR(1) model and observations Y can be modeled as a transfer function of X since the state of the second process step is dependent on the state of the first process step. To effectively distinguish and maintain the state of the two dependent process steps, the Shewhart control chart of residual and the cause-selecting control chart are proposed. The proposed control charts' performance is measured by the rate of alarm on the proposed charts. From numerical analysis, it shows that the performance of the proposed control charts is much better than the misused Hotelling T^2 control chart and the individual Shewhart X and Y control charts.

Keywords Autocorrelated observations · Control charts · Process variation · Residuals

1 Introduction

Control charts are first proposed by Shewhart [1], and become effective tools for improving the process quality and productivity.

A basic assumption in applications of control charts is that observations from the process at different times are independent random variables. However, the independence assumption is often violated for processes in chemical and pharmaceutical industries. Observations from these processes are always autocorrelated. When the control charts developed under the independence assumption, the autocorrelated process results in decreasing the in-control average run length (ARL). For effective monitoring the autocorrelated processes, one popular developed approach is to constructing control charts using the residuals from the time series model to the process data (see Abraham and Kartha [2], Alwan [3], Alwan and Roberts [4], Berthouex [5] Dooley, Kapoor, Dessouky and Devor [6], Delves [7], Ermer [8], Harris and Ross [9], Montgomery [10], Montgomery and Mastrangelo [11], and Wardell, Moskowitz, and Plante [12, 13]). The properties of the proposed residual charts and their performance are investigated by Harris and Ross [9], Longnecker and Ryan [14], Yashchin [15], Kramer and Schmid [16], Schmid [17], Lin and Adams [18], Schmid [19], Padgett, Thombs and Padgett [20], Runger, Willemain and Prabhu [21], Vander Weil [22], Timmer, Pignatiello and Longnecker [23], Schmid [24], Zhang [25], Schmid and Schone [26], Alwan and Roberts [27] and Lu and Reynolds [28].

Much of the paper on the performance of control charts based on residuals has focused on the Shewhart control chart of residuals.

Today, many industrial products are produced by several dependent process steps not just one process step. Consequently, it is not appropriate to monitor these process steps with a control chart for each individual process step; what is needed is an appropriate method for controlling the process steps. Zhang [29] proposes the simple cause-selecting chart to monitor the second step of the two dependent process steps effectively. Wade and Woodall [30] review the basic principles of the cause-selecting chart for two dependent process steps and suggest a modification to the use of simple cause-selecting chart. They also examine the relationship between the simple cause-selecting chart and the multivariate T^2 control chart. In their opinion, the simple cause-selecting control chart has some advantages over the T^2 control chart. Yang [31] designs economic control charts to monitor two dependent process steps with a single assignable cause. Yang [32] proposes an economic processes management

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method and applies it to the bank industry. Yang [33] proposes economic X and cause-selecting control charts to monitor two dependent process steps under a Weibull shock model. Yang [34] proposes a Markov chain approach to controlling over-adjusted process mean for two dependent process steps. Yang and Chen [35] extend Yang's model to two failure mechanisms with increasing failure rates. However, the above papers only consider the independent observations. The statistical process control approach to effectively distinguish and monitor the two dependent process steps for autocorrelated observations has not been addressed. In this paper, Shewhart chart of residuals and cause-selecting control chart are developed to effectively monitor the large mean shift on the first step and the large mean shift on the second step, respectively. The performance of the proposed control charts for monitoring and distinguishing the two dependent process steps is measured using the rate of false or true alarm. Finally, a numerical example illustrates the application of the proposed control charts, and its performance is compared with a misused T^2 chart and individual X and Y charts, respectively.

2 Autocorrelated observations for two dependent process steps

In this paper, we consider that a product is produced from two dependent process steps, where two types of failure mechanisms may occur to them. One type of the failure mechanisms may only occur to the first step and cause the shift of mean for the quality variable (X), while the other type occurs only at the second step and causes the shift of mean for the quality variable (Y). Two types statistical control charts will be derived to effectively distinguish and monitor the two dependent process steps with autocorrelated observations. Before describing how to derive the statistical control charts, the assumptions of the behavior of the production process steps are given as follows.

2.1 Assumptions

1. The production has two dependent process steps. They are the first step and the second step. The first step and the second step are dependent. Hence, the quality variable X produced by the first step will affect the quality variable Y produced by the second step. A pair of observations (x_t, y_t) can only be sampled from the end of the second step every h time unit of the sampling interval, $t = 1, 2, 3, \ldots$
2. For autocorrelated observations x_t at the first step, it is assumed that quality variable X_t can be written as an AR(1) model at time t with process mean ξ_X, that is

$$X_t = (1-\phi)\xi_X + \phi X_{t-1} + a_t, t = 1, 2, \ldots \quad (1)$$

where ϕ is the AR parameter satisfying $|\phi| < 1$. The a_t's are assumed to be independent normal random variables with mean 0 and variance σ_a^2.

Since X affects Y over time, the model relating the two variables can be written as a transfer function, that is

$$Y_t = C_Y + V_0 X_t + V_1 X_{t-1} + N_t, t = 1, 2, \ldots \quad (2)$$

where C_Y is a constant and where N_t's are assumed to be independent normal random variables with mean 0 and variance σ_N^2.
3. When one failure mechanism occurs only in the first step, it will shift the mean of X. This will also cause the mean of Y to shift, since Y is dependent on X. When the other failure mechanism occurs only in the second step, it will shift the mean of Y but the mean of X is unchanged.
4. Two control charts are constructed to monitor and distinguish the two dependent steps, and the time to sampling and charting one item is very small and negligible.

3 The time series model for autocorrelated process steps

The time series model, especially AR(1) model, has been widely used to model many types of processes. When the first process step is in control the minimum mean square error forecast (Box, Jenkins, and Reinsel [36]) made at time $t-1$ for time t is

$$\hat{X}_t = (1-\hat{\phi})\xi_{X0} + \hat{\phi} X_{t-1}. \quad (3)$$

The residual at time t is

$$e_{Xt} = X_t - \hat{X}_t. \quad (4)$$

Suppose that a failure mechanism would cause a step change from ξ_{X0} to ξ_{X1} in the process mean between time $t = \tau - 1$ and τ. The expectations of the residual for various times are

$$E(e_{Xt}) = \begin{cases} 0 & t = \tau-1, \tau-2, \ldots \\ \xi_{X1} - \xi_{X0} & t = \tau, \\ \phi^l(\xi_{X1} - \xi_{X0}) & t = \tau + l, \quad l = 1, 2, \ldots. \end{cases} \quad (5)$$

The residuals are uncorrelated and normally distributed with variance σ_a^2. We may find that the expectation of a residual after the shift occurs is a decreasing function of the time after the shift. Hence, the rate of a true alarm by a control chart of residuals in the first step is the highest for the sample immediately after the shift, and this rate continually decreases over time as the forecast adapts to the shift.

In the second step, a transfer function is used to express the relationship between quality variables Y and X. The estimate for Eq. 2 is

$$\hat{Y}_t = \hat{C}_y + \hat{V}_0 X_t + \hat{V}_1 X_{t-1}. \quad (6)$$

The residual at time t is

$$e_{Yt} = Y_t - \hat{Y}_t. \quad (7)$$

Suppose that another failure mechanism would cause a step change from ξ_{Y0} to ξ_{Y1} in the process step mean between time $t=\tau'-1$ and τ'. The expectations of the residuals for various times are

$$E(e_{Yt}) = \begin{cases} 0 & t=\tau'-1, \tau'-2, ..., \\ \xi_{Y1}-\xi_{Y0} & t=\tau', \\ 0 & t=\tau'+l, \quad l=1,2,\ldots . \end{cases} \tag{8}$$

The residuals are uncorrelated and normally distributed with variance σ_N^2. Note that the shift of mean only appears at time τ' after the failure mechanism occurs between time $\tau'-1$ and τ'.

4 Control charts construction

A general form of control charts is represented as follows.

$$\mu_W \pm k\sigma_W, \tag{9}$$

where μ_W and σ_W are the mean and standard deviation of a control statistic, say W_t, when the process is in control. The constant, k, is chosen to give a specified in control false alarm probability. The k is frequently taken to be 3 to give a false alarm probability 0.0027 for a Shewhart type control chart.

To monitor the first step, the used control chart is thus constructed based on the distribution of the in-control control statistic, e_{Xt}. From Eq. 5, the control limits of the Shewhart control chart of residuals are

$$\pm 3\sigma_a. \tag{10}$$

The control statistic, e_{Xt}, is thus plotted on the chart to determine if the first step is in statistical control.

Usually, the variance of the control statistic is unknown. The $\hat{\sigma_a} = \frac{\overline{MR_X}}{d_2}$ is adopted as its estimate, where $\overline{MR_X} = \frac{\sum_{t=1}^{n-1} MR_{X(t-1)}}{n-1}$, $MR_{X(t-1)} = |e_{Xt}-e_{X(t-1)}|$, $t=2,3,\ldots,n$, and the value coefficient d_2 is dependent on sample size ($n=2$).

To monitor the second step, it is incorrect to construct the control chart based on the distribution of quality variable Y, since quality variable Y is affected by quality variable X. The proposed approach is to monitor the specific quality in the second process by remove the effect of X from Y; that is the specific quality is presented by the cause-selecting values ($e_{Yt} = Y_t - \hat{Y}_t$). The cause-selecting control chart is thus constructed by the in-control distribution of cause-selecting values. That is, from Eq. 8, the control limits of the cause-selecting control chart are

$$\pm 3\sigma_N. \tag{11}$$

The control statistic, e_{Yt}, is thus plotted on the chart to determine if the second step is in statistical control.

Similar to estimate the variance of the control statistic e_{Yt}, the estimate of σ_N is $\hat{\sigma_N} = \frac{\overline{MR_Y}}{d_2}$, where $\overline{MR_Y} = \frac{\sum_{t=1}^{n-1} MR_{Y(t-1)}}{n-1}$, and where $MR_{Y(t-1)} = |e_{Yt}-e_{Y(t-1)}|$, $t=2,3,\ldots,n$.

Consequently, the Shewhart control chart and cause-selecting control chart are derived to effectively distinguish and monitor the process states of the first step and the second step.

Thus the control limits of the two proposed control charts can be expressed, respectively, as

$$\pm 3\frac{\overline{MR_X}}{d_2}, \tag{12}$$

and

$$\pm 3\frac{\overline{MR_Y}}{d_2}. \tag{13}$$

5 Performance measurement for the proposed control charts

The performance of a control chart can be measured by the rate of alarm on a control chart. The rate of a false alarm is the probability of a false alarm occurring on the control chart before a failure mechanism occurs in the process, and the rate of a true alarm is the probability of a true alarm occurring on the control chart after the failure mechanism occurs in the process and before it is removed. When the process is out of control it is desirable to have a higher rate of true alarm so that the change of the process mean will be detected quickly, and when the process is in control it is desirable to have a lower rate of false alarm. The probability of alarm for the developed two control charts will be calculated when both the two process steps are in control and when either one of or both the process means shift.

5.1 Calculating the probability of alarm for the two proposed control charts

The probability of false alarm for the Shewhart chart of residuals is 0.0027, and the same for the cause-selecting chart. To monitor the two dependent processes, two developed charts are used simultaneously. Hence the probability of at least one false alarm for the two charts is 0.0054, that is $1-0.9973\times 0.9973$. To calculate the probability of true alarm for the two proposed charts, we have to compute the probabilities of true alarms for the Shewhart chart of residuals and cause-selecting chart, respectively. Let the probability of true alarm for the Shewhart chart at time t be Ps_t, and the probability of true alarm for the cause-selecting chart at time t be Pc_t, then

$$\begin{aligned} Ps_t &= \Pr(e_{Xt} > 3\frac{\overline{MR_X}}{d_2} \text{ or } e_{Xt} < -3\frac{\overline{MR_X}}{d_2} | \phi^l(\xi_{X1}-\xi_{X0})) \\ &= 1-\Phi_S\left(3-\frac{d_2\phi^l(\xi_{X1}-\xi_{X0})}{\overline{MR_X}}\right) \\ &\quad +\Phi_S\left(-3-\frac{d_2\phi^l(\xi_{X1}-\xi_{X0})}{\overline{MR_X}}\right), \\ t &= \tau+l, l=0,1,2,\ldots \end{aligned} \tag{14}$$

$$Pc_t = \Pr(e_{Yt} > 3\frac{\overline{MR_Y}}{d_2} \text{ or } e_{Yt} < -3\frac{\overline{MR_Y}}{d_2} | (\xi_{Y1} - \xi_{Y0}))$$
$$= 1 - \Phi_C\left(3 - \frac{d_2(\xi_{Y1} - \xi_{Y0})}{\overline{MR_Y}}\right)$$
$$+ \Phi_C\left(-3 - \frac{d_2(\xi_{Y1} - \xi_{Y0})}{\overline{MR_Y}}\right),$$
$$t = \tau' \tag{15}$$

where Φ_S and Φ_C are the cumulative standard normal probabilities, respectively.

Note that the probability of true alarm from the Shewhart chart of residuals is decreasing over time, but not for the cause-selecting chart. Hence the probability of true alarm from at least one of the proposed charts will be decreasing over time, once the first process is out of control.

There are four situations for the out-of-control processes. The four situations associated with the probability of true alarm from the two proposed charts are described as follows.

1. The first process step is out of control but the second process step is in control.
   The probability (Psc_t) of a true alarm only from the residual control chart is

   $$Psc_t = Ps_t, t = \tau + l, l = 1, 2, 3, \ldots .$$

2. The first process step is in control but the second process step is out of control.
   The probability (Psc_t) of a true alarm only from the cause-selecting chart is

   $$Psc_t = Pc_t, t = \tau'.$$

3. The first process step is out of control after time $\tau - 1$, and the second process step is out of control after time $\tau' - 1$, where $\tau < \tau'$.
   The probability (Psc_t) of at least one true alarm from the residual control chart and the cause-selecting chart is

   $$Psc_t = \begin{cases} Ps_t, & \tau \le t < \tau' \\ 1 - (1 - Ps_t) \bullet (1 - Pc_t), & t = \tau', \\ Ps_t, & \tau' + l < t, l = 1, 2, 3, \ldots . \end{cases}$$

4. The first process step is out of control after time $\tau'' - 1$, and the second process step is out of control after time $\tau' - 1$, where $\tau'' > \tau'$.
   The probability (Psc_t) of at least one true alarm from the residual control chart and the cause-selecting chart is

   $$Psc_t = \begin{cases} Pc_t & t = \tau', \\ Ps_t & t \ge \tau''. \end{cases}$$

6 A numerical example and some comparison results

A quality engineer found that there is a large variability for the thickness of the thin golden films. From the quality data analysis, he found that the thickness of the thin golden films (Y) in the second process step was primarily affected by gold concentration (X) in the first process step. Two independent machines, say machine 1 and machine 2, may fail and influence the mean of the gold concentration and thickness respectively. Since the unacceptable mean of the thickness may be influenced by machine 2 or gold concentration. To effectively maintain the variability of the gold concentration and thickness and distinguish which process step is out of control, two control charts are constructed as described before.

To construct the proposed control charts, 100 paired observations (X_t, Y_t) are sampled from the end of the second process step. The 100 observations for X_t, $t = 1, 2, \ldots, 100$, are found autocorrelated and a time series model AR(1) is fitted. The fitted model is

$$\hat{X}_t = 4.0562 + 0.6102 X_{t-1}. \tag{16}$$

The residual (e_{X_t}) is calculated by $X_t - \hat{X}_t$, and the Shewhart chart of the residuals is constructed (Fig. 1). All plotted points (e_{X_t}, $t = 1, 2, \ldots, 100$) are within the control limits of the chart. Hence, the Shewhart chart of the in-control residuals, with upper control limit=5.39576, lower control limit $= -5.39576$ and center line $= 0$, can be used to monitor the future variability of the gold concentration in the first process step. Then, the relationship between (X_t, Y_t) is investigated (Fig. 2). It shows that they are related over time or on sampling number. Hence a time series model, transfer function, is fitted. The fitted transfer func-

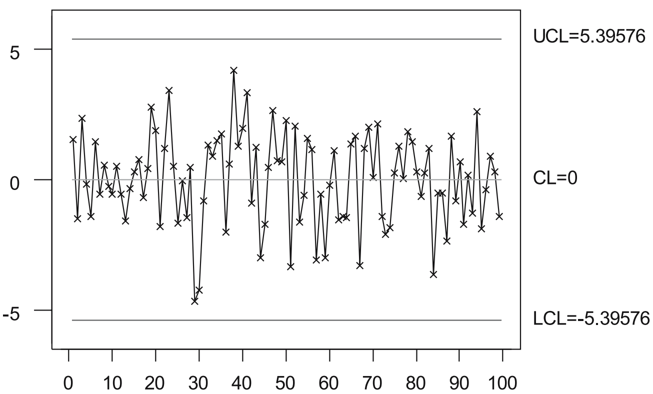

Fig. 1. Shewhart chart of residual

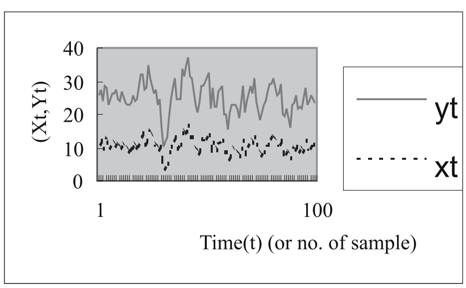

Fig. 2. The relationship between Xt and Yt on time

tion is

$$\hat{Y}_t = 3.16 + 1.0023X_t + 0.0967X_{t-1}. \quad (17)$$

The cause-selecting value (e_{Y_t}) is calculated by $Y_t - \hat{Y}_t$, and the cause-selecting control chart is constructed (Fig. 3). All plotted points (e_{Y_t}, $t = 1, 2, \ldots, 100$) are within the control limits of the cause-selecting control chart. Hence, the cause-selecting chart of the in-control cause-selecting value, with upper control limit $= 2.9432$, lower control limit $= -2.9432$, and center line $= 0$, can be used to monitor the future variability of the thickness in the second process step.

To measure the performance or detecting ability of the two proposed control charts, 51 additional paired samples (X_t, Y_t), $t = 1, 2, \ldots, 51$, are taken from the end of the second process step. The 51 paired values ($e_{X_t} = X_t - \hat{X}_t$, $e_{Y_t} = Y_t - \hat{Y}_t$), are calculated using Eqs. 16 and 17, and then plotted on the constructed Shewhart chart of the residuals and cause-selecting control chart respectively (Figures 4 and 5). It is found that points 21 and 22 fall outside of the control limits of the Shewhart chart of the residuals and point 19 falls outside of the control limits of the cause-selecting control chart. It indicates that the first process step is out of control on point 21 and 22 and machine 1 has to be adjusted, and the second process step is out of control on point 19 and machine 2 has to be adjusted.

Suppose that the quality engineer misuses Hotelling T^2 control chart or Shewhart individual X and Y control charts to monitor the two dependent process steps, the performance of them is worse. The performance of the two proposed control charts can be evaluated by comparing with Hotelling T^2 control chart and Shewhart individual X and Y control charts. First, we construct Hotelling T^2 chart (e.g., see Montgomery [10]) for the 100 paired observations (X_t, Y_t). The upper control limit of the T^2 chart is 11.829 with false alarm probability 0.0027. The 100 values of T^2 statistic are calculated and plotted on the T^2 chart (Fig. 6). All points are within the control limits, so the T^2 chart with upper control limit $= 11.829$, can be used to control the future state of the second process with bivariate quality characteristics. The additional 51 values of T^2 statistic are calculated and plotted on the constructed T^2 chart (Fig. 7). We found that only point 19 is out

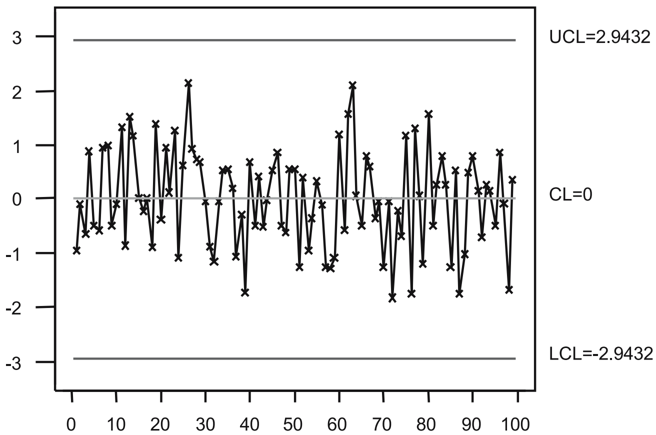

Fig. 3. Cause-selecting chart

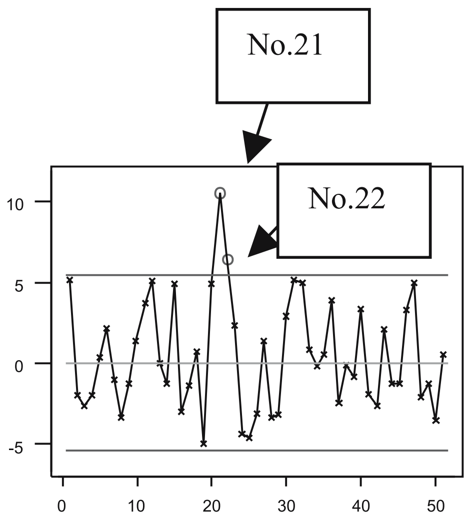

Fig. 4. Monitoring result of Shewhart chart of residual

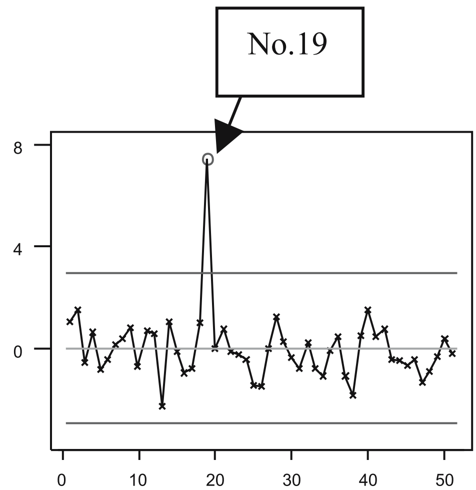

Fig. 5. Monitoring result of cause-selecting chart

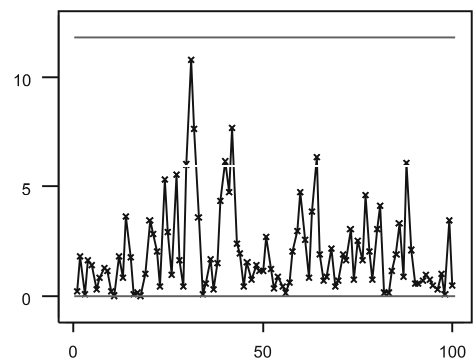

Fig. 6. Hotelling T^2 chart

of control and it cannot distinguish which process step is out of control. It is obvious that the performance of our proposed charts are better. Secondly, we construct Shewhart individual X chart for the first 100 observations (X_t) and Shewhart individual Y chart for the first 100 observations (Y_t) (Figures 8 and 9). Since some points fall outside of the control limits of the Shewhart individual X and Shewhart individual Y chart respectively, hence the outliers are removed and the control limits of the individual X and individual Y chart are re-calculated until all points fall within the control limits. Consequently, the control limits of the individual X chart and individual Y chart are (UCL = 14.44, CL = 10.45, LCL = 6.47) and (UCL = 19.37, CL = 14.71, LCL = 10.05), respectively (Figures 10 and 11). The additional 51 values of X_t and Y_t are thus plotted on the constructed individual X and individual Y chart (Figures 12 and 13). We found that many points fall outside of the control limits of the two individual charts. That is, the two in-

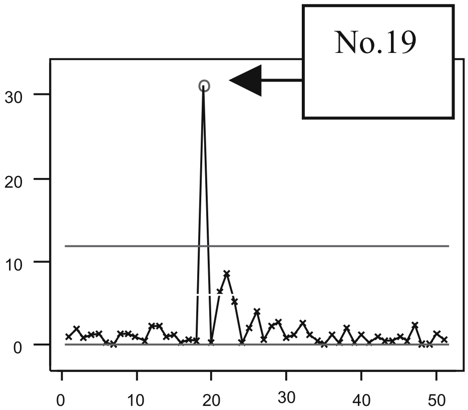

Fig. 7. Monitoring result of Hotelling T^2 chart

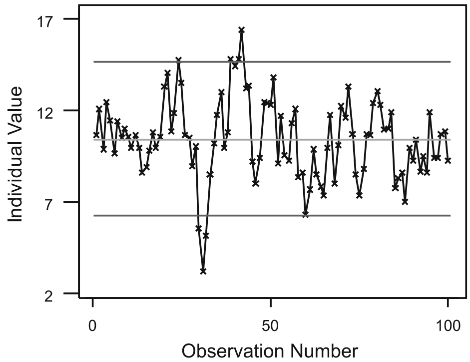

Fig. 8. Individual X control chart

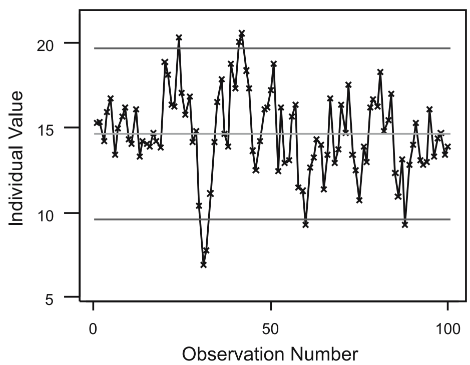

Fig. 9. Individual Y control chart

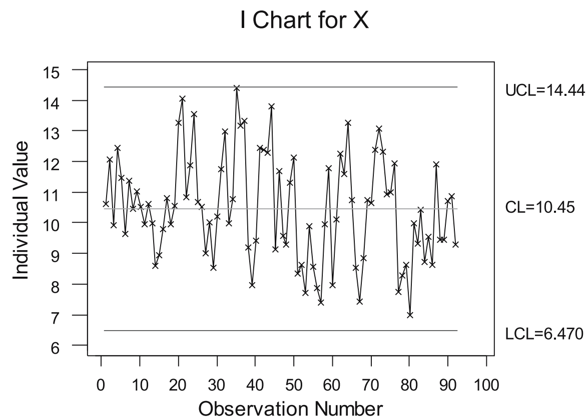

Fig. 10. In-control individual X control chart

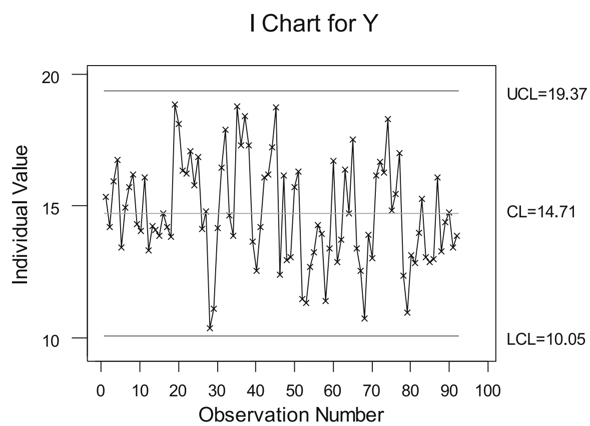

Fig. 11. In-control individual Y control chart

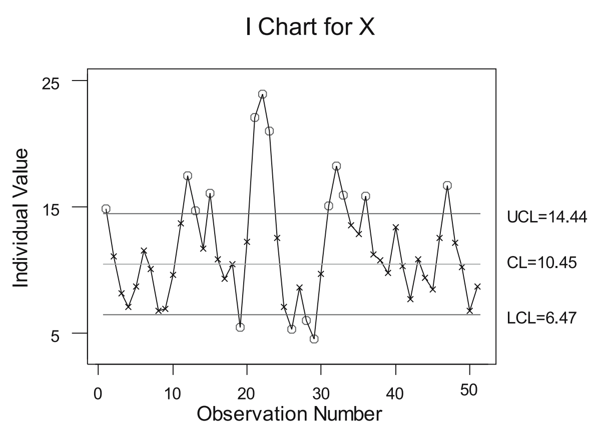

Fig. 12. Monitoring result of individual X control chart

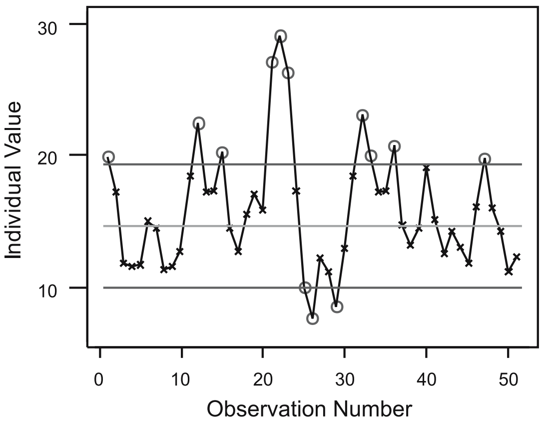

Fig. 13. Monitoring result of individual *Y* control chart

dividual charts give many false alarms and this would lead the quality engineer to over adjust the two dependent process steps.

It is obvious that our proposed control charts may effectively distinguish the out-of-control points on the first process step and the second process step, respectively. The T^2 chart can only detect the out-of-control plotted point and cannot distinguish which process step is out of control for the autocorrelated observations. The individual *X* chart and individual *Y* chart show many false alarms, respectively. Hence, they cannot effectively detect the autocorrelated observations on the two dependent process steps.

7 Summary

In the paper, the statistical process control approach to effectively distinguish and monitor the dependent process steps with autocorrelated observations is proposed. The Shewhart chart of residuals is used to monitor the shift of the process mean on the first process step and the cause-selecting control chart is developed to monitor the mean shift of the second process step. The performance of the proposed control charts for monitoring the two dependent process steps is measured by the probability of true alarm when at least one of the process steps is out of control. Finally, a numerical example illustrates the application of the proposed control charts, and their performance is demonstrated better than the Hotelling T^2 control chart and two individual *X* and *Y* control chart when the observations on the two dependent process steps are autocorrelated. Several important extensions of the developed approach can be developed. It is straightforward to extend the proposed approach to study other control charts for small shift of process means on the dependent process steps, like EWMA, CUSUM, or charts for attributes. The differences between the approaches lie in the derivation of the probabilities of type I and type II errors. One particularly interesting research area for future research involves the process control for correlated observations with the ARMA model under two dependent process steps and the adaptive process control for correlated observations with the ARMA model under two dependent process steps.

References

1. Shewart W (1931) Economic control of quality of manufactured product. Van Nostrand, Princeton, NJ
2. Abraham B, Kartha CP (1979) Forecast stability and control charts. ASQC Tech Conf Trans, Am Soc Qual Control, pp 675–685
3. Alwan LC (1991) Autocorrelations: fixed and versus variable control limits. Qual Eng 4:167–188
4. Alwan LC, Roberts HV (1988) Time-series modeling for statistical process control. J Bus Econ Stat 6:87–95
5. Berthouex PM, Hunter WG, Pallesen L (1978) Monitoring sewage treatment plants: some quality control aspects. J Qual Technol 10:139-149
6. Dooley KJ, Kapoor SG, Dessouky MI, Devor RE (1986) An integrated quality systems approach to quality and productivity improvement in continuous manufacturing processes. Trans ASME J Eng Ind 108:322–327
7. Delves LM, Mohamed JL (1985) Computational methods for integral equations. Cambridge University Press, New York
8. Ermer DS (1980) A control chart for dependent data. ASQC Tech Conf Trans Am Soc Qual Control, pp 121–128
9. Harris YJ, Ross WH (1991) Statistical process control procedures for correlated observations. Can J Chem Eng 69:48–57
10. Montgomery DC (2001) Introduction to statistical quality control, 3rd edn. Wiley, New York
11. Montgomery DC, Mastrangelo CM (1991) Some statistical process control methods for autocorrelated data. J Qual Technol 23: 179-193
12. Wardell DG, Moskowitz H, Plante RD (1992) Control charts in the presence of data correlation. Manage Sci 38:1084–1105
13. Wardell DG, Moskowitz H, Plante RD (1994) Run length distributions of special-cause control charts for correlated processes. Technometrics 36:3–17
14. Longnecker MT, Ryan TP (1992) Charting correlated process data. Technical Report No.166. Department of Statistics. Texas A & M University. Collage Station, TX
15. Yashchin E (1993) Performance of CUSUM control schemes for serially correlated observations. Technometrics 35:37–52
16. Kramer H, Schmid W (1997) Control charts for time series. Nonlinear Anal 30:4007–4016
17. Schmid W (1995) On the run length of a Shewhart chart for correlated data. Stat Papers 36:111–130
18. Lin WS, Adams BM (1996) Combined control charts for forecast-based monitoring schemes. J Qual Technol 28:289–301
19. Schmid W (1997a) CUSUM control schemes for Gaussian processes. Stat Papers 38:191–217
20. Padgett CS, Thombs LA, Padgett, WJ (1992) On the α-risks for Shewhart control charts. Commun Stat-Simul Comput 21:1125–1147
21. Runger GC, Willemain TR, Prabhu S (1995) Average run lengths for CUSUM control charts applied to residuals. Commun Stat-Theory Methods 24:273–282
22. Vander Well SA (1996) Modeling processes that wander using moving average models. Technometrics 38:139–151
23. Timmer DH, Pigantkiello JJ, Longnecker M (1998) The development and evaluation of CUSUM-based control charts for an AR(1) process. IIE Trans 30:525–534
24. Schmid W (1997b) On EWMA charts for time series, in Frontiers of statistical quality control. In: Lenz HJ, Wilrich P-T (eds) Physica-Verlag, Heidelburg
25. Zhang NF (1997) Detection capability of residual control chart for stationary process data. J Appl Stat 24:363–380
26. Schmid W, Schone A (1997) Some properties of the EWMA control chart in the presence of autocorrelation. Ann Stat 25:1277–1283
27. Alwan LC, Radson D (1992) Time-series investigation of subsample mean chart. IIE Trans 24:66–80

28. Lu C, Reynolds M (1999) EWMA control charts for monitoring the mean of autocorrelated processes. J Qual Technol 31: 166–188
29. Zhang G (1984) A new type of control charts and a theory of diagnosis with control charts. World Qual Congress Trans, Am Soc Qual Control, pp 75–85
30. Wade R, Woodall W (1993) A review and analysis of cause-selecting control charts. J Qual Technol 25:161–169
31. Yang S (1997) The economic design of control charts when there are dependent process steps. Int J Qual Reliab Manage 14:606–615
32. Yang C (1999) Economic process management and its application on bank industry. Qual Quant 31:381–394
33. Yang S (2003) Optimal processes control for a failure mechanism. Commun Stat 4:1285–1314
34. Yang S (2003) Dependent processes control for over-adjusted process means. Int J Adv Manuf Technol (in press)
35. Yang S, Chen Y (2003) Processes control for two failure mechanisms. J Chin Inst Ind Eng 20:481–493
36. Box G, Jenkins G, Reisel G (1994) Time series analysis, forecasting and control. Prentice-Hall, Englewood Cliffs, NJ