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A NOTE ON STATISTICAL MONITORING OF ENGINEERING CONTROLLED PROCESSES

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The importance of Statistical Process Control (SPC), also called Statistical Process Monitoring (SPM) techniques, for quality improvement is well-recognized in industry. With advances in sensing and data collection technology, large volumes of data are being routinely collected under Engineering Process Control (EPC) or Automatic Process Control (APC). There is a great need for SPC for variation reduction and quality improvement in these environments. This research studies the statistical properties of monitoring the process output and the control action of EPC controlled processes. Several statistical monitoring strategies are introduced and their advantages and disadvantages are discussed.

Keywords: Statistical Process Control; Engineering Process Control; Multivariate Control Charts; Time Series.

1. Introduction

As manufacturing quality has become a decisive factor in global market competition, Statistical Process Control (SPC), also called Statistical Process Monitoring (SPM) technique, is becoming very popular in industries. Many manufacturing processes, which are equipped with Engineering Process Control (EPC) or Automatic Process Controls (APC), are implementing SPC to a different extent.

Many manufacturing processes are equipped with EPC, which is for short-term variation reduction only. A process change may be compensated by EPC, but if the root causes of the change are not detected and identified, a continued departure from the nominal may happen repeatedly. Moreover, as EPC can mask process defects, failures, and drifts, this may lead to eventual catastrophic failures. Thus, for long-term process improvement, it is crucial to utilize SPC for EPC controlled processes to detect significant changes in the process.

Using SPC to monitor the special causes of a process along with EPC is known to be a major tool for on-line quality improvement.[1–3] It can achieve the following tasks. First, it can verify the continued adequacy of EPC scheme. SPC can detect the inadequacy of the control scheme which may increase the process variation and affect the output quality. Second, it can signal significant changes in the process from past performance. Also, it can help identify root causes of changes in performance.[4]

Although SPC techniques are currently used, the existing methods cannot effectively monitor and detect changes in EPC controlled processes. This is partly because that EPC may cause the process output to adapt to the changes and there is only a limited "window of opportunity" to detect process changes. All the existing SPC techniques suffer from this problem. The limitations of conventional SPC techniques will be discussed in Sec. 2.

SPC is traditionally applied to processes in which successive observations are assumed to be independent and identically distributed (i.i.d.). In practice, EPC controlled processes often violate the i.i.d. assumption, and the presence of autocorrelation has a serious impact on the performance of control charts.[5,6] In the existing literature, all the autocorrelated SPC studies are focused on processes without EPC. One raw-data monitoring approach is to modify the control limits of traditional charts to achieve an acceptable rate of false alarms resulting from the trending behavior inherent in most autocorrelated processes.[7] A forecast-error monitoring approach uses special cause charts (SCC) proposed by Alwan and Roberts.[8] As the forecast errors are uncorrelated if the forecast model is correct, conventional control charts can then be applied to them. However, SCC still may not detect special causes effectively, especially when the process is positively autocorrelated.[9,10] Tsung, Shi, and Wu[11] pointed out that the monitoring of EPC controlled processes, which is different from the auto-correlated SPC, has some unique features: (i) it has more complicated auto-correlated structures due to EPC; (ii) the EPC control parameters have impacts on the SPC performance; (iii) the correlation between the input and output needs to be considered.

More research is needed to utilize the engineering/physical information contained in EPC and to establish the relationships among the controlled output and input, the model parameters, and the control parameters. These relations/models will provide a basis for deriving SPC schemes that incorporate both auto- and cross-correlation in the inherent process, i.e., the predictable part of the process. These SPC schemes will be used to detect the process change due to special causes, i.e., the unpredictable part of the process. The correlation issue will be tackled in Sec. 3.

In many controlled processes, the only monitored variable, if any, is the controlled output.[3] Monitoring the controlled outputs alone may not be sufficient because the process changes can be compensated by control actions and are therefore hard to detect from the process outputs. Tsung *et al.*[11] proposed a joint monitoring scheme using Hotelling's approach and Bonferroni's approach for a EPC-controlled process. Tsung[12] also extended this idea to monitor input-output combinations using principle component monitoring.

Both individual monitoring and combined monitoring of the process output and the control action will be described and discussed in Secs. 4 to 6. In Sec. 6, the advantages and disadvantages of several statistical monitoring strategies will also be discussed. This paper ends with some concluding remarks in Sec. 7.

2. Limitations of Conventional Control Charts

In this section, we illustrate the limitations of conventional control charts, such as the Shewhart charts, for an EPC-controlled process. We consider an integral (I) control scheme,

$$x_t = k_I \sum_{j=0}^{t} e_j \tag{1}$$

where e_j is the amount of deviation from process mean at time j and the constant k_I determines the amount of cumulative (integral) adjustment. It is a special case of Proportional-Integral-Derivative (PID) control schemes,[13–15] and is one of the most popular EPC schemes. It is also equivalent to the minimum mean squared error (MMSE) control scheme of a first order integrated moving average (IMA) disturbance process. The integral control produces a control action that is proportional to the sum of the output error. It is known in control theory that once a step change or mean shift is added to the system, this control can reduce or eliminate the static error, that is, the steady state magnitude of the process output $E(e_t) \simeq 0$.[16]

The reason is as follows. Here the integral control action is $x_t = x_{t-1} + k_I e_t$. Suppose the control parameters are within the stability region, that is, the controlled process is asymptotically stable to a step change or mean shift in the input. Thus, x_t is nearly constant, i.e., $x_t \simeq x_{t-1}$, which leads to the conclusion that the expected value $E(e_t)$ approaches zero.

It is desirable to eliminate the static magnitude of the error of the process output from the viewpoint of EPC, but it is not good to mask the detection of out of control conditions from the viewpoint of the statistical monitoring. As the information contained in the dynamics of the process outputs is ignored in conventional SPC, the detection of the mean shifts would mainly depend on the steady state magnitude $E(e_t)$, which is reduced to zero under an integral control.

Thus, conventional SPC is not very useful in detecting the out-of-control conditions such as mean shifts as long as it has missed the transient period right after mean shifts occur. This is also realized as a "window of opportunity" for out-of-control detection by the process output.[17] All the conventional SPC techniques suffer from the same problem.

3. Analogy to Forecast-Error Monitoring

The study of SPC for EPC-controlled processes has been scanty. We will demonstrate the relationship between the forecast-error monitoring in autocorrelated SPC schemes and the monitoring of an EPC-controlled process, and show their analogy. Consider an observation d_{t+1} generated by a time series process. We make a one-step-ahead forecast $\hat{d}_{t+1}$, which is to be a function of current and previous observations d_t, $d_{t-1}, \ldots$. The forecast error at time $t+1$ is

$$e_{t+1} = d_{t+1} - \hat{d}_{t+1} \,. \tag{2}$$

On the other hand, we consider an EPC-controlled process with a simple dynamic model $y_{t+1} = x_t$, which means that y_{t+1} at time $t+1$ depends on the control action x_t at time t. Let d_{t+1} be the disturbance at time $t+1$. Then the process output at time $t+1$ is

$$e_{t+1} = y_{t+1} + d_{t+1} = x_t + d_{t+1} \,. \tag{3}$$

Suppose $\hat{d}_{t+1}$ was some estimate of d_{t+1}, which could be made at time t. Then a realizable form of control could be obtained by setting

$$x_t = -\hat{d}_{t+1} \,. \tag{4}$$

Then the process output at time $t+1$ is

$$e_{t+1} = d_{t+1} - \hat{d}_{t+1} \,, \tag{5}$$

which is equal to the "forecast error". Therefore, the monitoring of forecast errors is equivalent to monitor the process output with a corresponding EPC control rule. It is known that the EPC control rule corresponding to the MMSE forecast is the MMSE control, and the EPC control rule corresponding to the exponentially weighted moving average (EWMA) forecast is the integral (I) control.[18] Wardell *et al.*[6] and Vander Wiel[17] pointed out the ineffectiveness of forecast-error monitoring in many cases. This is equivalent to pointing out the ineffectiveness of EPC-controlled process output monitoring.

Vander Wiel[17] also pointed out the superiority of cumulative sum (CUSUM) charts over Shewhart charts in monitoring the forecast errors of an IMA(0,1,1) process. Note that CUSUM charts monitor the cumulative sum of e_t

$$z_t \sim \sum_{j=0}^{t} e_j \,, \tag{6}$$

although in practice, we accumulate only the excess over a critical value k to reduce false alarms.

For an IMA(0,1,1) disturbance process with its corresponding MMSE control, which is integral control in this case, the control action is the cumulative sum of current and previous process outputs multiplied by a constant k_I as in (1). We now realize that monitoring z_t in Eq. (6) is analogous to monitoring x_t in Eq. (1), thus the superiority of CUSUM charts for the forecasting errors may be used to predict the superior performance of the control action monitoring.

4. Monitoring the Control Action

MacGregor[19] suggested that it may be useful to monitor the control action, as the occurrence of a special cause such as a mean shift would lead to some larger control actions than usual. Faltin and Tucker[20] and Faltin *et al.*[21] also addressed the issue of control action monitoring. This idea was followed by Messina *et al.*[24] for an integrated EPC/SPC system and Tsung *et al.*[11] for a throttle position sensor (TPS) assembly process.

If there is a shift in the process mean, a corresponding control action is needed to bring the process back to the normal state. The rate of such application can be instantaneous or gradual depending on the EPC controller. Thus, the feasibility and efficiency of control action monitoring depends on the design of EPC controller, the estimation of control action variance, and the determination of SPC control limits. Although control action monitoring may be one possible solution to overcome the limitations of conventional SPC, no one pointed out the reason why it is a promising alternative when output monitoring is ineffective. This may be explained by the finding that disturbance variation and process change can be transferred from the process output to the control action in a EPC controlled process: we consider an EPC controlled process with the same dynamic model as in the previous section. Let the disturbance d_t be described by an autoregressive moving average (ARMA(1,1)) model:

$$d_t = a_t(1 - \theta B)/(1 - \phi B) \tag{7}$$

where $|\phi| < 1$ and $|\theta| < 1$, and a_t represents white noise. Let B be the usual backward shift operator, i.e., $Ba_t = a_{t-1}$. This model represents a large number of stationary disturbance processes in industry.[22] Also, it is approximately an IMA(0,1,1) model when its autoregressive parameter ϕ is close to 1. Note that the process variation before implementing EPC is

$$\sigma_d^2 = \sigma_a^2(1 + \theta^2 - 2\phi\theta)/(1 - \phi^2)\,. \tag{8}$$

Then the process output after EPC is

$$e_{t+1} = y_{t+1} + d_{t+1} = x_t + d_{t+1}\,. \tag{9}$$

The MMSE control scheme under an ARMA(1,1) disturbance is given by Box *et al.*[22]

$$x_t = e_t(\theta - \phi)/(1 - \phi B)\,. \tag{10}$$

Note from Eq. (10), when $\phi = \theta$ this control scheme suggests no control: $x_t = 0$. This is because the ARMA(1,1) disturbance process reduces to i.i.d. white noise when $\phi = \theta$,[22] thus in this situation the best suggested control action is not to adjust the process, which is consistent with Deming's philosophy.[23] With MMSE control, we can see from Eqs. (9) and (10)the variation of process output σ_e^2 significantly reduces to σ_a^2. On the other hand, the variation of the control action x_t is

$$\sigma_x^2 = \mathrm{var}(a_t(\theta - \phi)/(1 - \phi B)) = \sigma_a^2(\phi - \theta)^2/(1 - \phi^2)\,. \tag{11}$$

Then from Eqs. (8) and (11) it can be shown that

$$\sigma_x^2 = \sigma_d^2 - \sigma_e^2$$

which explains the "missing" variation in the process (see Table 1).

Table 1. The Variation Transfer due to MMSE Control for an ARMA(1,1) Disturbance Process.

Variation	Before EPC	After EPC
Variation of the Process Output	σ_d^2	σ_a^2
Variation of the Control Action	0	$\sigma_d^2 - \sigma_a^2$
Total Process Variation	σ_d^2	σ_d^2

Thus, the monitoring of the control action identifies another opportunity to detect unexpected process change and large process variation, which may be missed by the monitoring of the process output.

The monitoring of the MMSE control action under an ARMA(1,1) disturbance process has been studied by Messina *et al.*[24] As the control action is usually correlated, they suggest monitoring the forecast errors of the control action. We consider a shift in the process mean μ_t is introduced to an ARMA(1,1) process as a single step change starting at time 0. Hence, from Eqs. (9), (7) and (10), the process output is

$$e_t = \mu_t(1 - \phi B)/(1 - \theta B) + a_t\,. \tag{12}$$

We can see that e_t reduces to a_t as $\mu_t = 0$.

To monitor the forecast errors of x_t, we obtain the MMSE forecast of x_t by Box *et al.*,[22]

$$\hat{x}_t = \phi x_{t-1}\,. \tag{13}$$

Thus, from Eqs. (10), (12), and (13), the forecast error of x_t is

$$x_t - \hat{x}_t = (\theta - \phi)\left(\frac{1 - \phi B}{1 - \theta B}\mu_t + a_t\right)\,. \tag{14}$$

Comparing Eqs. (12) and (14), we can see that the forecast error of the MMSE control action is proportional to the process output with scale change. Therefore, there is no difference between monitoring the process output and the forecast errors of the control action.

However, as we pointed out earlier that in some cases the monitoring of the control action is superior to that of process output, so some of the information for detection is definitely missing after subtracting the one-step MMSE forecast of the control action. As it is not desirable to ignore any of the information for detection from the observations, the forecast error monitoring of the control action is not recommended in practice. Instead, we suggest directly monitoring the control action with modified control limits.

5. Monitoring Either the Input or the Output

Although we show the superiority of monitoring the control action in some situations, the performance of monitoring the control action is not always better than that of monitoring the process output. Different disturbance processes may lead to very different performance of both the input and output monitoring.

To give more insight into their properties, simulated examples of ARMA(1,1) disturbance processes with MMSE control are provided. The disturbance processes are generated according to Eq. (7), with a shift of $2\sigma_d$ in the mean introduced at time zero. The observed control actions and process outputs are calculated by Eqs. (9) and (10). The control actions and the process outputs are monitored by separate individual Shewhart charts. The performance of these charts is measured by their average run length (ARL), which is the average number of time periods before indicating an out-of-control condition (i.e., an observation falls outside the control limits). The ARL for an in-control process is called ARL_0, and the ARL for an out-of-control process is called ARL_1.

The control limits for the process output monitoring are set at $\pm 3\sigma_a$ to have an ARL_0 of about 370. This is equivalent to false alarm rate of 0.27%. As the control actions are correlated, the control limits for the control action monitoring are modified to be $\pm(\phi - \theta)/\sqrt{1-\phi^2}L\sigma_a$ by (11), where L is determined through simulation to obtain an ARL_0 of about 370. In this study, the modified constants L range from 2.86 to 2.87, which depend on ϕ and θ.

Here a 2 by 2 full factorial design with four different combinations of the ARMA(1,1) parameters ϕ and θ is run to investigate the entire parameter space. Note that the objective here is to compare the performance of the input and output monitoring under different disturbance processes. A guideline to suggest a suitable monitoring scheme will be provided later. Since it is frequently observed that the ϕ value is larger than the θ value,[25] the experimental ϕ values are chosen to be -0.8 and 0.8, and the experimental θ values are chosen to be -0.5 and 0.5. Each process is simulated 10,000 times in order to obtain the ARL value. Their performances are summarized in Table 2.

Figures 1(a1) to 1(d2) show Shewhart charts for the control actions and the process outputs, and the dashed lines show the corresponding deterministic mean shifts. Note that after EPC, the mean of the process outputs is no more a sustained step change, but a shift with dynamic pattern, as is the mean of the control actions.

Example (a) is simulated from an ARMA(1,1) process with $\phi = 0.8$ and $\theta = 0.5$. From Fig. 1(a2), for the monitoring of the process outputs there is a mild overshoot of the deterministic mean shift at the beginning, but the transient period is very

Table 2. Summary of ARL Results of the Simulated Examples.

	ARMA(1,1) Parameter		Control Action Monitoring		Process Output Monitoring	
Ex.	ϕ	θ	ARL_0	ARL_1	ARL_0	ARL_1
(a)	0.8	0.5	370.4	7.6	370.4	40.9
(b)	0.8	−0.5	370.6	10.3	370.4	4.6
(c)	−0.8	0.5	370.2	1.5	370.4	1.0
(d)	−0.8	−0.5	370.4	56.2	370.4	2.9

short. The steady state magnitude of the process outputs gradually approaches a small constant, so a Shewhart chart is not useful, and its ARL_1 value is 40.9. In this case, the mean shift was detected in 24 observations.

From Fig. 1(a1), for the monitoring of the control actions, there is no overshoot, but the steady state magnitude is very large. Thus, it is effective to detect out-of-control conditions by monitoring the control actions in this situation, and its ARL_1 value is 7.6. In this case, the mean shift was detected in nine observations. For the disturbance processes near this parameter region, the monitoring of the control actions is preferred to the monitoring of the process outputs.

Example (b) is simulated with $\phi = 0.8$ and $\theta = -0.5$. The process output monitoring in Fig. 1(b2) shows there is a larger overshoot than that in Fig. 1(a2), which may lead to fast detection of out-of-control conditions, so its corresponding ARL_1 value is small. However, the steady state magnitude is quite small right after a short transient period. In this case, the Shewhart chart missed the window of opportunity and could not detect the mean shift within 50 observations. The control action monitoring in Fig. 1(b1) shows there is a large steady state magnitude after the transient period. Thus, as in Example (a), it is also effective to detect out-of-control conditions by monitoring the control actions in this situation. In this case, the mean shift was detected at the 16th observation.

Example (c), with $\phi = -0.8$ and $\theta = 0.5$, demonstrates a situation where both the control action monitoring and the process output monitoring are effective, as both ARL_1 values are within 2. In both Figs. 1(c1) and 1(c2), the overshoots are large and the steady state magnitudes are even larger than the original magnitude of the mean shift. These results are caused by the large negative autocorrelation of the disturbance process. In this case, the mean shift was detected within three observations in both charts.

Example (d), with $\phi = -0.8$ and $\theta = -0.5$, shows a opposite situation to Examples (a) where the process output monitoring is more effective. From Fig. 1(d1), both the overshoot and the steady state magnitude of the control action observations are small, so it is not effective to detect out-of-control conditions by monitoring the control actions, and its corresponding ARL_1 value is 56.2. In this case the Shewhart

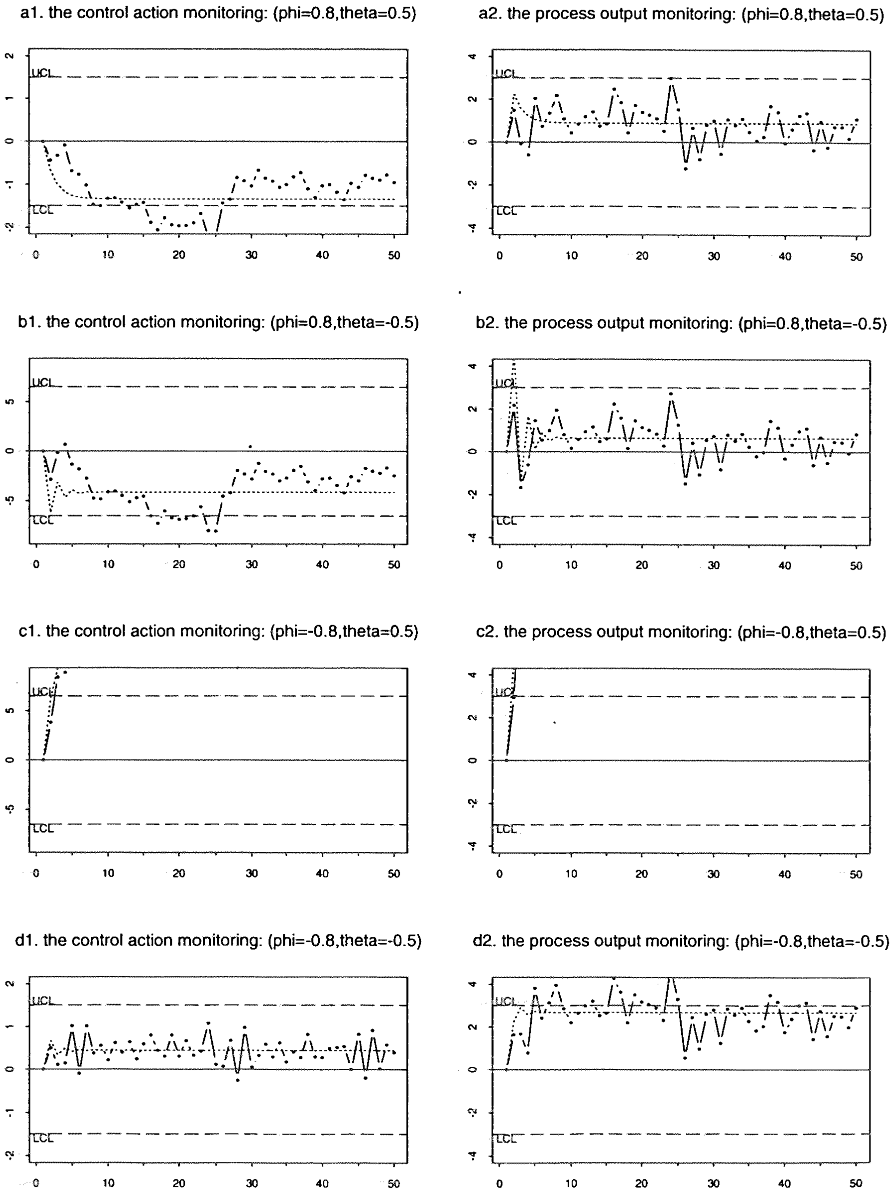

Fig. 1. Shewhart Charts of the MMSE control actions and Shewhart Charts of the Process Outputs for Four Simulated ARMA(1,1) Disturbance Processes. Dashed lines show their corresponding deterministic mean shifts.

chart of the control action monitoring can not detect the mean shift within 50 observations. On the other hand, from Fig. 1(d2), its overshoot is small, but the steady state magnitude is very large. Thus, it is quite effective to detect out-of-control conditions by monitoring the process outputs, and its ARL_1 value is 2.9. Here the mean shift was detected at the fifth observation. For the disturbance processes near this parameter region, the monitoring of the process outputs is preferred to the monitoring of the control actions.

6. Joint Monitoring Strategies

In practice, we usually do not know whether monitoring the process output or monitoring the control action is better unless the process model is exactly known. Here joint monitoring strategies taking into consideration both the process output and the control action are shown to be more robust and more promising methods. Several joint monitoring strategies are described as follows, and their pros and cons are discussed.

6.1. *Combined monitoring of the output and the forecast error of the control action*

A straight-forward strategy is to use one SPC chart to monitor the process output and use another SPC chart to monitor the control action. The out-of-control condition is detected when one of the charts is signaled. Messina *et al.*[24] suggest the combined monitoring strategy to monitor the forecast error of the control action using tracking signals[26] and an EWMA chart, and simultaneously monitoring the process output using a Shewhart chart or an EWMA chart.

This strategy is simple and straightforward. No controller information is needed. However, as discussed before, the forecast error monitoring of the control action is not recommended because some of the information for detection is missing after subtracting the one-step forecast of the control action. Also, the issue of false alarms generated by their monitoring strategy is not studied in their paper. It is known that if two separate charts are used simultaneously, their overall type I error will increase, i.e., their overall false alarm frequency will increase.[27] The overall false alarm problem can be controlled by Bonferroni's approach in Sec. 6.2.

6.2. *Bonferroni's approach*

Bonferroni's approach is to use two Shewhart charts to monitor the process output and the control action simultaneously. It also uses Bonferroni's inequality to modify the control limits to ensure the value of the overall type I error.[28] If the controller and disturbance parameters are known, the control limits can be calculated.[11] Otherwise, they can also be determined via historical process data.

This strategy is the simplest multivariate SPC method, and it gives acceptable false alarm frequency. Tsung *et al.*[11] show that for the situations with small correlation between the input and output, Bonferroni's approach may outperform the other multivariate SPC methods such as Hotelling's approach. This conclusion can be extended to the other Bonferroni-type charts, such as the Multivariate CUSUM charts by Woodall and Ncube,[29] which monitor each of the quality characteristics individually with CUSUM charts.

However, it is known to be a conservative approach because it does not give exact type I errors. It is even less powerful as it does not use the information of the covariance structure between the control action and the process output.

6.3. *Hotelling's approach*

Hotelling's approach is to monitor the Hotelling's T^2 statistics of the control action and process output.[30] It measures the overall distance of the observations from the reference values. This approach requires knowledge of the covariance matrix between the input and output. If the controller and disturbance parameters are known, the covariance matrix can be derived.[11] In other cases, the covariance matrix is estimated from the historical data, but its distribution shifts from a χ^2 to an F distribution.

This is a popular multivariate SPC method due to its optimal property. Hawkins[31] pointed out that based on standard multivariate theory, the optimal affine invariant test statistic for a shift in the mean vector of the single observation vector to some other unspecified vector is the Hotelling's T^2 statistic. Hotelling's approach is superior to Bonferroni's approach in that the former gives exact type I errors while the latter gives conservative type I errors. Tsung *et al.*[11] show that in the situations with large correlation between the input and output, Hotelling's approach may dominate. This conclusion can be extended to the other Hotelling-type charts, such as the multivariate CUSUM charts by Alwan,[32] which monitor a CUSUM of the T^2 statistics.

However, Hotelling's approach requires the extra knowledge of the covariance $\sigma_{e,X}$. If the calculation of $\sigma_{e,X}$ from the estimated model would incur a significant error, its advantage may be eroded and may even perform worse than the other SPC methods.

6.4. *Principal component monitoring*

Sometimes multivariate SPC charts are not feasible for industrial practitioners. It may be more desirable and practical to use conventional univariate SPC methods such as a Shewhart chart to monitor a combination of the input and output. Principal component analysis (PCA) techniques are suggested to identify the best linear combination of the output and control actions for applying conventional SPC charts.

This approach is more economical and easier to implement as it only needs conventional univariate SPC charts such as Shewhart charts. The PCA model to obtain the input-output combination can be built up by historical data.[33] However, as in Hotelling's approach, the principal component monitoring strategy also requires the knowledge of the covariance structure between the control action and the process output. It is possible that the covariance structure, i.e., the relation between the control action and the process output, may change with time, as may its associated PCA model. Thus, Tsung[12] proposes an adaptive principal component monitoring scheme to update the PCA model adaptively by monitoring the residual, i.e., the squared prediction error of new input-output observations.

7. Conclusion

Partly because of the renewed interests in the integration of SPC and EPC, the statistical monitoring of EPC-controlled processes is shown to be an important issue for both academic and industrial practitioners. The consideration of some commonly used EPC and disturbance models, in this paper, is a starting point for such studies, and its study may shed some light on the general problem.

In this paper, limitations of conventional control charts for an EPC controlled process are illustrated by exploring the "window of opportunity" problem. The analogous relation between the forecast-error monitoring in autocorrelated SPC schemes and the monitoring of an EPC controlled process is demonstrated. The variation transfer between the process output and the control action during EPC is also identified. To conquer these identified limitations and problems, several joint monitoring strategies are introduced, such as the combined monitoring of the output and the forecast error of the control action, the Hotelling's approach, the Bonferroni's approach, and the adaptive principal component monitoring.

Note that a goal of these monitoring schemes is to identify root causes of variability and changes in the system, with the purpose of properly correcting for these and gaining a fundamental understanding and improvement of EPC-controlled process. Exactly how the detection, isolation, and identification of the root causes should be conducted under the integrated environments of SPC and EPC warrants further research.[34]

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