Integrating Statistical Process Control and Engineering Process Control

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Statistical process control (SPC) is traditionally applied to processes that vary about a fixed mean, and where successive observations are viewed as statistically independent. Engineering process control (EPC) is usually applied to processes in which successive observations are related over time, and where the mean drifts dynamically. Thus, EPC seeks to minimize variability by transferring it from the output variable to a related process input (controllable) variable, while SPC seeks to reduce variability by detecting and eliminating assignable causes of variation. This paper shows through simulation that when using EPC it is always better to have an SPC system in place that monitors and acts properly on the root cause of the assignable change.

Introduction

STATISTICAL process control (SPC) and engineering process control (EPC) are two strategies for quality improvement that have developed independently. Box and Kramer (1992) provide an excellent comparison of SPC (which they refer to as statistical process monitoring) and engineering process control (which they refer to as automatic process control (APC)). They mention that the origin of statistical process monitoring was in the parts industry, whereas APC had its origins in the process industry. They give several reasons why disparities between the two industries, and hence means of controlling critical process variables, are becoming smaller.

In general, both techniques have reduction of variability as their objective, although they seek to accomplish these objectives in different ways. SPC looks for signals representing assignable causes, which may be thought of as external disturbances that increase variability. Most SPC techniques assume that the process data can be described in terms of statistically independent observations that fluctuate around a constant mean. On the other hand, EPC actively reverses the effect of process disturbances by making regular adjustments to manipulatable process variables. EPC is usually discussed in the framework of a process with a drifting mean, and the objective of the process adjustments is to keep the output quality characteristic on target. EPC essentially accomplishes this by transferring variability in the output variable to an input control variable.

There is usually a difference in the implementation strategy for these two techniques. SPC is often a "top-down" tool, driven by upper management (or customers) as part of a company-wide quality im-

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provement process, while EPC is often a "bottom-up" procedure, driven by process control or manufacturing engineers. In effect, the role of SPC is to change the process when assignable causes occur, and the role of EPC is to continually adjust the process to counteract ongoing forces that will cause the process to drift off-target if compensations are not made. Hence, SPC does not control the process, but rather performs a monitoring function that signals when control, in the form of identification and removal of the root causes, is needed. On the other hand, EPC does not remove the root or assignable causes; it uses continuous adjustments to keep process variables on target. We will present a case for the use of both statistical monitoring and engineering control on process variables of interest.

Until recently, there has been little effort to integrate monitoring and engineering control strategies. However, such integration is useful because improved quality performance is the likely result. An integrated system can use EPC to reduce the effect of predictable quality variations and SPC to monitor the process for detection of assignable causes. The elimination of these assignable causes will result in additional reduction of overall variability. Important references that discuss or illustrate this concept include MacGregor (1987, 1988); Faltin, Hahn, and Tucker (1989); and Vander Weil, Tucker, Faltin, and Doganaksoy (1992). MacGregor and Harris (1990) have emphasized the importance of using control charts to monitor the performance of EPC schemes. Messina (1992) provided additional discussion of these concepts.

The purpose of this paper is to demonstrate the potential effectiveness of integrating SPC and EPC in a reasonably general situation. Specifically, we use a modification of the funnel experiment as described by MacGregor (1990) and show how simple SPC methods applied to the output deviation from target can greatly reduce variability when assignable causes occur.

The Process Model

MacGregor (1990) presented an instructive view of the funnel experiment studied extensively by Deming (1950). In this experiment a ring stand is placed over a level surface that is marked with a target "bull's eye". A funnel is mounted to the stand and marbles are dropped through the funnel. After each drop the ring stand is moved according to one of several rules. The rules proposed by Deming are the following.

1. Leave the funnel fixed and aimed at the target
2. If the distance from the resting place of the marble to the target is Y, then move the funnel a distance $-Y$ from its current position
3. The same as rule 2, but move the funnel a distance $-Y$ from the target
4. Move the funnel to the resting place of the marble just dropped.

Deming (1986, 1993) summarized the results with these four rules. Rule 1 always produces the best results, namely, a stable distribution of marble positions with minimum variance. Rule 2 produces a stable distribution, but the variance is twice that obtained with rule 1. Under rule 3, the system explodes. The marble will eventually move away from the target in two (opposite) directions in a symmetrical pattern. Rule 4 also results in the marble moving away from the target, but it moves in one direction and behaves like a random walk.

The results of applying rules 2, 3, and 4 have been used by Deming and others to demonstrate what will happen when one "tampers" with a stable process. This leads to the obvious question, "When do we tamper with (i.e., adjust) the process, and when do we leave the process alone?". The answer is that SPC will tell the decision-maker when to look for assignable causes (and make adjustments) and when to leave the process alone.

MacGregor demonstrated analytically and illustrated by simulation that if the process mean is fixed, control actions will be worse than no control, but with a drifting process mean even rule 2 yields a smaller mean square error than no control. He also showed that the minimum mean square error (MMSE) controller will, except for extreme cases, always outperform the no control situation.

Note that with rule 2 the funnel position immediately before the t^{th} marble is dropped is equal to the sum of all previous adjustments, and therefore, this control rule is what is referred to as integral control with a gain of unity. Integral control applications have long been used in the process industries. In fact, they have been referred to as the main-stay of control for processes. Integral control is characterized by rapid gain, that is, quick responses by the controlled variable to controller adjustments. Uses of integral controllers include moisture control on the dryer in an instant coffee process and adjustments of chlorine gas flow to pulp mass in a bleach plant. In the discrete parts areas, cutting tool manufacturers are beginning to provide integral controllers to manipulate the position of the cutting tool based on the deviation of the cut path from target. Of course, integral control is just one type of engineering control, and other types of engineering control, long prevalent in the process industries, are now being applied in the parts industries as well.

MacGregor, when considering the case of a drifting mean, used the model

$$Y_t = u_{t-1} + n_t + e_t \tag{1}$$

where Y_t is the output of the process at time period t, u_{t-1} is the effect of any control action taken after the $(t-1)^{\text{st}}$ observation, n_t is the effect of the underlying disturbances on the true process mean at time t, and e_t is an independent random variable with mean zero and variance σ_e^2. In the context of the funnel experiment, Y_t is the position of the marble after the t^{th} drop, u_{t-1} is the position of the funnel after the $(t-1)^{\text{st}}$ control action, and n_t is the underlying process shift at the t^{th} drop. The quantities n_t are assumed to follow an autoregressive process of order one (i.e., an AR(1) process). That is,

$$n_t = \phi n_{t-1} + a_t \tag{2}$$

where $-1 < \phi < 1$ and the a_t's are random variables with mean zero and variance σ_a^2 that are independent of one another and of the n_t's. The sequences a_t and e_t are assumed to be independent. Time series models of the autoregressive, moving average type, of which model (2) is an example, are discussed in many texts including Box and Jenkins (1976) and Montgomery, Johnson, and Gardiner (1990).

The model given by equations (1) and (2) describes a process with a drifting mean, such as is widely encountered in the chemical and process industries. In such applications one would typically find $\phi > 0$ and values of ϕ approaching unity are not unusual. For the process model with a drifting mean described by equations (1) and (2), MacGregor (1990) suggested the control action

$$u_t = \phi u_{t-1} - (\phi - \theta) Y_t \tag{3}$$

where θ $(0 \le \theta \le +1)$ is the moving average parameter in the first-order autoregressive moving average (or ARMA(1, 1)) model that results when the AR(1) model in equation (2) is combined with the white noise term e_t in equation (1). For more details, see Anderson (1976, p. 146), Box and Jenkins (1976), and MacGregor and Harris (1993, p. 110). These authors point out that the sum of an AR(1) process and white noise is ARMA(1, 1), and they also discuss estimation of θ. MacGregor (1990) gave an equation relating θ to ϕ, σ_e^2, and σ_a^2.

The control action of equation (3) is based on using the MMSE controller as discussed by Box and Jenkins (1976). MacGregor (1990) showed that this EPC rule gives superior performance to no control when $\theta > 0$. He also provided some graphical illustrations. There are many other types of controllers including adaptive, feedforward, and feedback. Each is appropriate under certain conditions. However, the MMSE controller is an industry standard.

These results assume that there are no assignable causes present. The only sources of disturbances are the motion in the mean from equation (2) and the random disturbance term e_t in equation (1). We now investigate how this system operates when additional assignable causes occur. We will assume that this model is appropriate and that the statistical monitoring scheme will only signal external changes (i.e., assignable causes). If however, either the model is inappropriate, such as mis-specified parameters (discussed by Box and Kramer), or if the parameters of the model change over time, then the SPC procedure may not function properly.

Applying SPC to the output deviation from target can result in rapid detection of assignable causes, and if the assignable causes are eliminated, considerable reduction in output variability can be obtained. The assignable causes take the form of either a sudden shift in the process mean or a trend in the mean. Using EPC alone will be compared with using EPC coupled with SPC. It should be mentioned that EPC rules can be devised to accommodate anticipated process disturbances (e.g., a trend in the mean). We incorporate no such rules here and assume that the EPC scheme was developed only to account for autocorrelation in the mean. Assignable causes are typically unanticipated, and this is assumed to be the case in the developments that follow.

An Example

We first show a simple example and then give the results of a more comprehensive simulation study. Figure 1 shows the output for 500 observations of the process under the model given by equations (1) and (2) with the control actions given by equation (3). The parameter values are $\phi = 0.95$ and $\theta = 0.4$, which are the same as those used by MacGregor (1990). The values of these parameters are

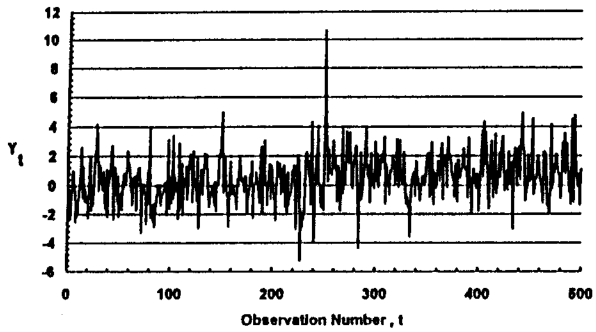

FIGURE 1. Output Deviations From the Target Using EPC. A Shift of 10 Units Occurs at $t = 251$ and PM = 3.14.

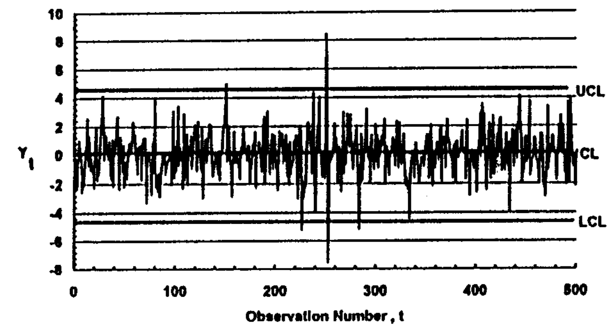

FIGURE 3. Output Deviations From the Target Using EPC and a Shewhart Chart for Individuals. A Shift of 10 Units Occurs at $t = 251$ and PM = 2.68.

certainly not all-encompassing, but they are typical of those encountered in practice. In fact, the overwhelming majority of process plant data encountered by the authors indicates that when the AR(1) model is appropriate, the value of ϕ is between 0.7 and 1.0. For values of ϕ in this interval we would expect results to be similar to those reported here.

At time $t = 251$ a disturbance consisting of a sustained shift of magnitude 10 units was introduced into the process. The MMSE controller compensates for this assignable cause to a large degree. Figure 2 shows the resulting control actions from equation (3). The performance measure we used was the average squared deviation from the target (T). That is,

$$\mathrm{PM} = \frac{1}{n}\sum_{t=1}^{n}(Y_t - T)^2 \tag{4}$$

where in this case $T = 0$ and $n = 500$. For the EPC rule in Figure 1, PM = 3.14.

Figure 3 shows the process output assuming that in addition to the EPC rule a Shewhart chart for individuals is applied to the output deviation from target. The Shewhart limits are shown on the graph. Note that there is a false action signal (below the lower limit) almost immediately after the shift at $t = 251$. Assuming that the assignable cause is eliminated as soon as it is detected the performance measure for the realization in Figure 3 under the combined EPC/SPC procedure is PM = 2.68. Thus, the combined procedure provides a substantial reduction in variability. Figure 4 shows an exponentially weighted moving average (EWMA) control chart with $\lambda = 0.1$ applied to the output deviation from target. The EWMA control chart applies a weight of λ to the most recent observation and geometrically decreasing weights to the prior observations in order to obtain the point to be plotted on the chart. Specifically, at time t one plots

$$Z_t = \lambda Y_t + (1 - \lambda) Z_t.$$

The EWMA control chart was explained in detail

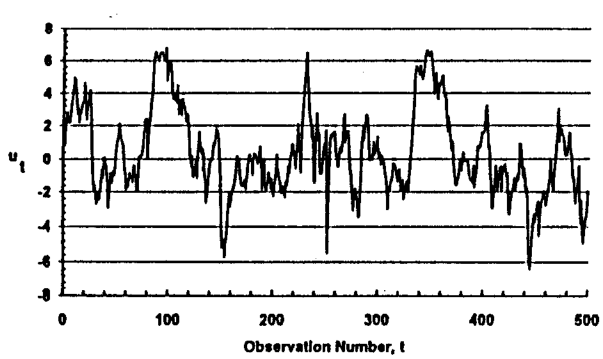

FIGURE 2. Control Actions for the Process in Figure 1.

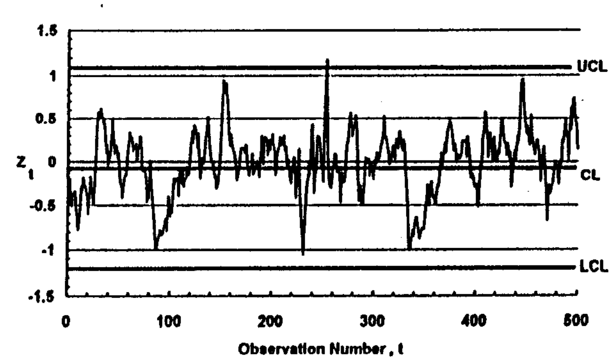

FIGURE 4. An EWMA Control Chart Applied to the Output Deviation From the Target With $\lambda = 0.1$. A Process Shift of 10 Units Occurs at $t = 251$.

by Hunter (1986). As in the case of the Shewhart chart, the EWMA control chart quickly detects the assignable cause, and if it is immediately eliminated, the performance measure is PM = 2.87. Once again, this is an improvement in comparison to the use of only the EPC rule.

Assignable causes may take forms other than sustained shifts. Suppose that an assignable cause resulting in a trend impacted the process model given by equations (2) and (3). Figure 5 shows the result of this type of assignable cause on the output, assuming that the trend per period is of magnitude unity and that the control rule of equation (3) is employed. Clearly, this control rule is now ineffective. Unless some other engineering action is taken, the process will drift completely away from the target. While it is highly unlikely that such a drift would be tolerated or allowed to continue for very long, we calculated, purely for comparison purposes, the performance measure for all 500 observations as PM = 90.74.

Figure 6 shows the process output with the Shewhart chart for individuals applied to the output deviation from target. Once again the assignable cause is quickly identified, and if it is immediately removed, the performance measure is PM = 3.29. Note that in this case the point below the lower control limit is not a false signal. It occurred because the upward shift was not detected immediately, and the feedback control algorithm overcompensated. Figure 7 shows the EWMA chart with $\lambda = 0.1$ applied to the output deviation from target. The performance measure for this procedure is PM = 2.81. This is smaller than the performance measure observed using the Shewhart chart because the EWMA detected the assignable cause slightly sooner.

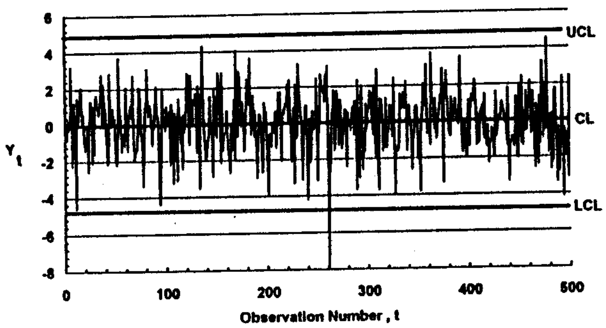

FIGURE 6. Output Deviations From the Target Using EPC and a Shewhart Chart for Individuals. A Trend of 1.0 Units per Period Starts at t =251 and PM = 3.29.

Simulation Results

To further investigate the performance of this integrated EPC/SPC system, two simulation studies were performed. The first simulation assumed that the assignable cause was a sustained shift. The shift magnitudes investigated were 1, 2, 5, 7.5, and 10 units. The second simulation assumed that the assignable cause resulted in a trend. The magnitudes of the trend were 0.05, 0.10, 0.25, 0.5, and 1.0 units/period. In each case the assignable cause occurred at period 251 and was eliminated as soon as it was detected by the SPC rule. Performance measure results were calculated across 500 periods. The EPC rule continued in operation for all 500 periods. The random variables e_t and a_t in equations (1) and (2) were assumed to be normally distributed and independent. Details of the random number generation procedure and the computer program are in Messina (1992).

Four different SPC control charts for the output deviation from target were investigated: a Shewhart

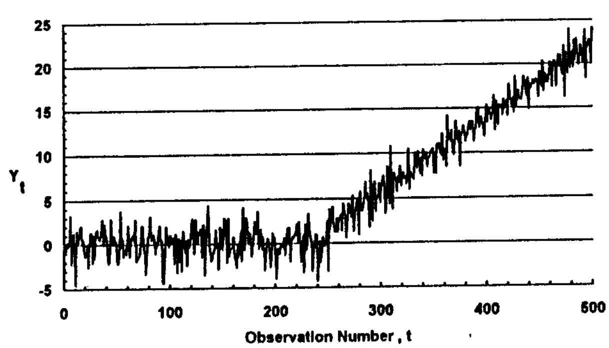

FIGURE 5. Output Deviations From the Target using EPC. A Trend of 1.0 Unit per Period Starts at t = 251 and PM = 90.74.

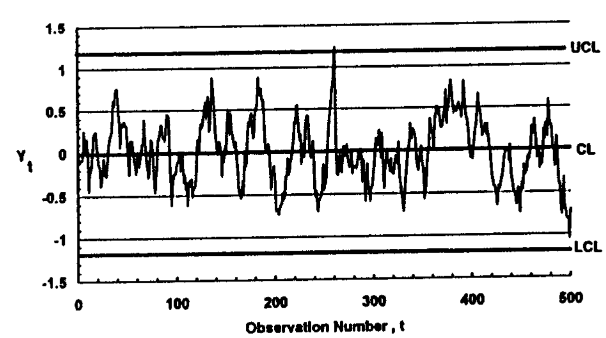

FIGURE 7. An EWMA Control Chart Applied to the Output Deviation From the Target With $\lambda = 0.1$. A Trend of 1.0 Units per Period Starts at t = 251.

chart for individuals with 3σ limits, an EWMA chart with $\lambda = 0.1$ and 3σ limits, an EWMA chart with $\lambda = 0.4$ and 3σ limits, and a cumulative sum chart (CUSUM) with $k = 0.5$ and $h = 5$. Details concerning the CUSUM chart can be found in Montgomery (1991). The EWMA weight $\lambda = 0.4$ was suggested by Hunter (1989), who showed that using this value produces nearly identical weights for current and previous observations as do the Western Electric rules. This EWMA does not have the same average run length performance as the Shewhart chart with the Western Electric rules, but it does use the process data in nearly the same way.

Some experimenters compare statistical monitoring schemes by selecting parameters of the schemes to yield the same in control ARL. However, we chose to select parameters that are either effective across a range of process shifts such as the CUSUM with $k = 0.5$ and $h = 5$ or result in properties similar to desirable schemes, such as the EWMA with $\lambda = 0.4$. Our intent is not to make explicit comparisons of the ARL performance of various SPC schemes, but instead to demonstrate that several widely used procedures operating with nominal design parameters work well in conjunction with engineering process control.

Table 1 presents the results for the sustained shift. The results reported are average values of the performance measure from equation (4) and the associated standard error (in parentheses) based on 2000 simulation runs. The first column gives the performance measure prior to introduction of the shift (i.e., for periods 1-250). Each succeeding column gives the performance measure for period 251-500 for either the EPC rule or some combination of EPC and an SPC rule. Column one indicates that the performance measure prior to the shift is the same for all five shift sizes evaluated (as expected). The remaining columns imply that the combined EPC/SPC scheme has a smaller performance measure than the EPC rule alone. There is some indication that the Shewhart chart for individuals performs better than the other SPC charts for the larger shifts, specifically 7.5 and 10.0. We conclude that integrating an SPC rule with EPC by applying SPC to the output deviation from target results in reducing overall variability if assignable causes in the form of sustained shifts occur.

Table 2 presents the ARL's observed in the simulations from Table 1. The smallest shifts are most difficult to detect, as one would expect. One reason that the ARL's are so long for these small shifts is that with the EPC rule the effect of an assignable causes is converted from a step change in a correlated process to a patterned change in an uncorrelated process. When the shift associated with the assignable cause is small, active control will often largely compensate for it.

Table 3 presents simulation results analogous to those in Table 1, assuming that the assignable cause

TABLE 1. Averages of the Performance Measures for EPC/SPC Rules Based on 2000 Simulations. The Assignable Cause is a Shift in the Process Mean at Observation 251. Standard Deviations of the Performance Measure are Given in Parenthesis

Shift Magnitude	Prior to Shift	EPC	EPC and Shewhart	EPC and EWMA $\lambda = 0.1$	EPC and EWMA $\lambda = 0.4$	EPC and CUSUM $h = 5$, $k = 0.5$
1	2.538	2.638	2.552	2.552	2.552	2.552
	(0.0051)	(0.0062)	(0.0052)	(0.0053)	(0.0053)	(0.0052)
2	2.538	2.679	2.594	2.594	2.594	2.593
	(0.0051)	(0.0064)	(0.0052)	(0.0052)	(0.0052)	(0.0052)
5	2.552	2.929	2.754	2.811	2.793	2.785
	(0.0050)	(0.0077)	(0.0053)	(0.0054)	(0.0054)	(0.0053)
7.5	2.544	3.298	2.962	3.033	2.929	2.943
	(0.0045)	(0.0098)	(0.0056)	(0.0059)	(0.0058)	(0.0057)
10	2.544	3.838	3.094	3.273	3.111	3.311
	(0.0051)	(0.0123)	(0.0061)	(0.0066)	(0.0066)	(0.0061)

TABLE 2. Average Run Lengths for the Rules in Table 1. Standard Deviations of the Run Length are Given in Parenthesis

Shift Magnitude	EPC and Shewhart	EPC and EWMA $\lambda = 0.1$	EPC and EWMA $\lambda = 0.4$	EPC and CUSUM $h = 5$, $k = 0.5$
1	102.1 (1.60)	112.9 (1.62)	114.7 (1.71)	105.4 (1.72)
2	93.3 (1.61)	100.7 (1.59)	101.8 (1.69)	94.9 (1.71)
5	31.1 (1.31)	61.6 (1.48)	48.8 (1.60)	39.7 (1.31)
7.5	3.0 (0.34)	24.4 (0.94)	12.2 (0.90)	5.7 (0.43)
10	1.0 (0.0)	5.2 (0.31)	1.8 (0.23)	1.3 (0.04)

resulted in a trend of 0.05, 0.10, 0.25, 0.50, and 1.00 units per period. Once again, the combined EPC/SPC rule provided improved results in all cases when compared to only an EPC rule. There is an indication that the three non-Shewhart procedures provide more reduction in variability than does the Shewhart chart for individuals. The EWMA with $\lambda = 0.1$ and the CUSUM are particularly effective. The ARL's in Table 4 illustrate why this is so. The EWMA with $\lambda = 0.1$ and the CUSUM have ARL's that are considerably smaller than the other control rules when the magnitude of trend is 0.10 units per period or larger. Overall, the EWMA and CUSUM seemed to be the best process monitors. The choice between them is not critical since they behave quite similarly when "tuned" (i.e., adjusted) for specific shift conditions (see Lucas and Saccucci (1990)).

In some circumstances it may be better to monitor the control variable than the output. We have investigated the effect of applying the SPC procedure to the control actions of the manipulated variable (see Messina, Runger, Montgomery, and Keats (1994)) and found that better results were achieved with EPC/SPC than with EPC alone.

TABLE 3. Averages of the Performance Measures for EPC/SPC Rules Based on 2000 Simulations. The Assignable Cause is a Trend that Starts at Observation 251. Standard Deviations of the Performance Measure are Given in Parenthesis

Trend Magnitude Per Period	Prior to Trend	EPC	EPC and Shewhart	EPC and EWMA $\lambda = 0.1$	EPC and EWMA $\lambda = 0.4$	EPC and CUSUM $h = 5$, $k = 0.5$
0.5	2.555 (0.0050)	3.064 (0.0066)	2.872 (0.0076)	2.807 (0.0065)	2.963 (0.0077)	2.778 (0.0061)
0.10	2.534 (0.0051)	4.398 (0.0085)	3.519 (0.0206)	2.594 (0.0072)	2.594 (0.0144)	2.593 (0.0068)
0.25	2.543 (0.0051)	13.963 (0.0166)	4.085 (0.0304)	2.811 (0.0080)	3.467 (0.0155)	2.291 (0.0077)
0.50	2.557 (0.0051)	46.842 (0.0325)	4.165 (0.0309)	2.976 (0.0079)	3.413 (0.0154)	2.910 (0.0076)
1.00	2.551 (0.0051)	179.573 (0.0620)	3.814 (0.0261)	2.989 (0.0076)	3.122 (0.0113)	2.885 (0.0071)

TABLE 4. Average Run Lengths for the Rules in Table 3. Standard Deviations of the Run Length are Given in Parenthesis

Trend Magnitude Per Period	EPC and Shewhart	EPC and EWMA $\lambda = 0.1$	EPC and EWMA $\lambda = 0.4$	EPC and CUSUM $h = 5$, $k = 0.5$
0.05	119.9 (1.61)	119.8 (1.23)	149.2 (1.47)	111.8 (1.25)
0.10	109.7 (1.39)	73.5 (0.70)	109.2 (1.06)	68.3 (0.71)
0.25	60.8 (0.68)	33.9 (0.30)	49.5 (0.47)	31.6 (0.32)
0.50	32.1 (0.36)	17.4 (0.15)	24.2 (0.24)	15.8 (0.15)
1.00	14.3 (0.17)	9.1 (0.07)	10.0 (0.09)	7.8 (0.06)

Summary

The integrating of EPC and SPC has potentially desirable results. EPC can be used to minimize deviations from target due to disturbances that occur continuously and are part of the process itself, and SPC applied to the output deviation from target can be used to identify and subsequently eliminate assignable causes. As mentioned by Box and Kramer (1992), SPC is perhaps a misnomer, because control is introduced though EPC, and statistical process monitoring is a better description of the role of the statistical control chart.

We described and illustrated a simple method of integrating these two concepts. Using MacGregor's (1990) model of the funnel experiment, we showed that combined EPC/SPC control rules always result in reduction of overall variability if the system experiences certain external assignable causes. Both sustained shifts and trends were investigated. The results demonstrate that the addition of an SPC chart to monitor output deviation from target in a system with active (i.e., engineering) control is a simple but highly effective way to integrate these two strategies. We conclude that proper use of both SPC and EPC can always outperform the use of either alone.

The present study considered only the MMSE control rule. We have investigated other control models, including proportional-integral-differential (PID) control (see Keats, Montgomery, Runger, and Messina (1992)), and the combination of SPC/EPC was again quite effective. We concluded that in many chemical and process plants and in computer integrated manufacturing environments combining engineering control and statistical process monitoring is an important tool ready for use in the quality improvement process.

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