Title: Combining SPC and EPC in a hybrid industry. By: Janakiram, Mani, Keats, J. Bert, Journal of Quality Technology, 00224065, Jul98, Vol. 30, Issue 3

Database: Business Source Complete

Combining SPC and EPC in a Hybrid Industry

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SOURCE:Journal of Quality Technology 30 no3 189-200 Jl '98

ABSTRACT

Integration of statistical process control (SPC) and engineering process control (EPC) is finding wide recognition and is successfully used in continuous process industries. However, application of this technique to parts or hybrid industries involving both discrete part monitoring and continuous process monitoring, offers challenges due to rate of sampling, fault detection, real time compensation, and process control. This paper explains the difference between SPC and EPC in simple terms and presents a case study that demonstrates successful integration of SPC and EPC for a product in this industry.

Key Words: Engineering Process Control, Integral Control, Statistical Process Control, Time-Series Modeling.

INTRODUCTION

STATISTICAL process control (SPC), also known as statistical process monitoring, has been very widely used ever since it was introduced by Dr. Shewhart in the form of control charts. The main purpose of SPC is to look for assignable causes (variability) in the process data. If assignable causes are present, then they are indicated by a change in the mean or variance of the process. In such a case, the process or production engineer or, in some cases, the operator stops production, eliminates the assignable cause, and restarts the production cycle. Shewhart charts, CUSUM, and EWMA control charts are extensively used for the purpose of process monitoring. SPC has been proven to be effective, in the form of control chart use, for the parts industries as evidenced by over 60 years of successful applications. SPC in the process industries has had limited successes due to the nature of the process data, which is often autocorrelated.

Engineering process control (EPC) is one of the techniques very widely used in process industries which aims at keeping the process output variables on target. Here, EPC is used to monitor the process output, compare it with the target, and make compensatory adjustments to the process input on a regular basis to keep the output on target. The application of EPC is primarily in process industries since it relies on the autocorrelated structure of the output variable. Autocorrelated structures in process variables are becoming more common in the parts industries because of the ability to capture contiguous data quickly.

The combined SPC/EPC scheme is gaining recognition in the process industries where the process frequently experiences a drifting mean. Part of a recent text (Box and Luceño (1997)) illustrates conclusively through several examples that attempts are being made to apply SPC and EPC to hybrid processes that involve both discrete part monitoring and continuous process monitoring. It is to be noted that both SPC and EPC techniques have reduction of variability as their objective, although they use different ways to accomplish this objective. In an integrated system, EPC is used to reduce the effect of predictable quality variation, and SPC is used to monitor the process in order to detect assignable causes. An example provided by Montgomery (1996) shows situations where EPC is superior to SPC. In the example, the process of driving a car has the objective of keeping the car in the center of the lane or minimizing variation around the center of the lane. Here, the output variable is the car position relative to the center of the lane, and the manipulated variable is the steering wheel column. The driver understands the relationship between the output variable and the manipulated variable and makes regular adjustment to drive the car on target. It clearly can be seen that the only way the driver can reach his or her destination is by using a feedback control scheme (EPC) to control the car and not by using any SPC techniques. EPC does not make an attempt to identify assignable causes that may impact the process, but it reacts to process upsets. In the previous example, the assignable causes could be a worn tire, a drunk driver, etc. Integrating SPC with EPC will make significant process improvement, since EPC will keep the system on target and SPC will aim at eliminating assignable causes by monitoring the system. Figure 1 from Montgomery (1996) illustrates an effective methodology to combine SPC with EPC. There are other methodologies, for example, Algorithmic SPC (VanderWeil et al. (1992)) and Run by Run Control (Sachs, Hu, and Ingolfsson (1995)).

BACKGROUND

EPC is based on control theory which aims at keeping the process on target. It involves predicting the next observation in the process, identifying some other variable in the process that can be manipulated in order to affect the process output, and finally, determining and applying control action at time, t, based on the effect of this manipulated variable and on the predicted disturbance at time t + 1. A clear understanding of the process dynamics and the relationship between manipulated variable and output variable is essential to accomplish this task. Control theory accomplishes this task through the use of deterministic models, stochastic models, and transfer function models. The deterministic models are used to design the controller, and stochastic models, in the form of time series, are used to model the residual effects. The model equations are either proportional, integral, derivative, or a combination. The compensation is applied in the form of feedback, feedforward, or a combination of both. Bollinger and Duffie (1988) have explained various types of deterministic control schemes.

There have been disagreements between control engineers and statisticians regarding the effectiveness of EPC versus SPC. This is mainly due to the lack of knowledge about control systems on the part of the statisticians and the lack of knowledge of SPC on the part of the control engineers. Before any attempt is made to integrate SPC and EPC, it is very important for both control engineers and statisticians to gain a thorough understanding of the concepts involved. Since SPC and EPC represent two different control scenarios, it has been a challenge to integrate or use both techniques for process monitoring. However, lately there has been much more interest in this area since an effective integration of SPC and EPC is likely to result in improved quality through further reduction of variability. For example, Box and Luceño (1997) have demonstrated feedback control using bounded adjusted charts.

Messina (1992) has presented the differences between SPC and EPC in a tabular form (Table 1). Comparison of the two methodologies based on Table 1 indicates that SPC and EPC have nothing in common. However, MacGregor (1988) suggested that stochastic control theory connects these two fields.

The results of the Deming funnel experiment, which is explained in Evans and Lindsay (1996), have had major ramifications on the way the practitioners' view SPC and EPC. MacGregor (1990) has shown that the modified funnel experiment (rule #2) can be effectively used for process monitoring and control and hence, can be used in the integration of SPC/EPC strategy. As per Deming, rule #1 always produces the best results (accurate and precise); rule #2 is accurate, but not precise; rules #3 and #4 are neither accurate nor precise. The SPC techniques discussed in the introduction will work very well for Rule #1 types of processes. MacGregor argues that for a process with a drifting mean, rule #1 is not necessarily a good method, but rule #2 will work effectively. However, he suggested that a modification to rule #2 will work well since a 100% correction (deadbeat response) is very severe, meaning variability in the form of overcorrection to the system is a possibility. Hence, he recommends a less severe correction that corresponds to a correction of less than 100% of the difference between actual value and target value to be applied to the process. This technique uses a minimum mean squared error (MMSE) controller that, except for extreme cases, outperforms the no-control situation, particularly in the case of a drifting mean.

Astrom and Wittenmark (1984) provide a detailed presentation of stochastic control as applied to engineering process control. Stochastic control employs a model for the process dynamics and disturbance of a system. The presence of autocorrelated data and delays associated with analytical measurements are incorporated in the control strategy. Stochastic control differs from SPC in that a model of the process is required. The usual models chosen are the transfer function models as described in Box, Jenkins and Reinsel (1994). These deterministic disturbances can be modeled by steps, ramps, or sinusoidal functions. These deterministic models do not represent the process dynamics fully since they fail to consider the stochastic disturbance of the process. Autoregressive, integrated, moving average (ARIMA) time series models can be used to characterize the stochastic disturbances.

The combination of deterministic and stochastic components may be necessary to form the combined SPC/EPC scheme of control. MacGregor (1988) has shown that, for steady-state processes with non-zero control action costs, the SPC charting method can be optimal controllers. If there is no cost associated with control actions or if process dynamics exists, then discrete stochastic control theory provides a more powerful approach to quality control.

Integration of SPC and EPC will work well to reduce variability as shown by Montgomery, Keats, Runger, and Messina (1994). They demonstrated through simulation that, under shifts or drifts in the process mean, when using EPC it is better to have an SPC system that monitors and acts properly on the root cause of the assignable change.

MacGregor (1988) has indicated that there are two types of process disturbances, namely stochastic disturbances arising from random variations occurring continuously in many processes and deterministic disturbances that occur due to sudden step or ramp changes in a load variable at any particular instant of time. Load disturbances often occur randomly and infrequently in time, but their nature is well defined through deterministic models. Differential equations and transfer functions are used to model the deterministic disturbances and some of the simple models are pulse, step, ramp, and sinusoidal disturbance models. The stochastic disturbances can be either stationary or non-stationary. A stationary disturbance will be random, but will have a fixed mean. They are modeled using the autoregressive (AR) or autoregressive moving average (ARMA) time series models. A non-stationary disturbance is one that has no fixed mean or level, but exhibits a drifting or non-stationary behavior. Box, Jenkins, and Reinsel (1994) have shown that ARMA models can be made stationary by taking the difference between successive values and that the differenced data can be modeled by the stationary ARMA models. One of the most important non-stationary models is the integrated moving average process (IMA) that is very common in environments where SPC is used.

Usually one of the most important objectives in product quality control is to minimize the variance of the output deviations from the target or the set point. The steps involved to achieve this objective are identifying the process dynamics and disturbance models followed by designing a control algorithm to meet the above criteria. MacGregor (1988) explained Minimum Variance Controllers (MVC) with and without process dynamics. His conclusion is that, for pure gain or steady-state processes where there are non-zero costs associated with taking control actions, SPC charting methods can be optimal controllers. However, if there are no costs associated with taking control action or if there exist process dynamics, standard SPC charting can be far from optimal, and discrete stochastic theory provides a more general and powerful approach to quality control.

MMSE CONTROLLERS

Consider a simple process where Y[subt] is the output at time t(t = 0, 1, 2,..., n) that is expected to conform to the target, T, and where X[subt] is the process set-point. A control engineer would like to ignore the stochastic nature of the disturbance, as it would be easier to model deterministic process dynamics with difference equations and transfer function models. However, stochastic disturbances are a reality, and given this fact, a designer of a controller would like to apply compensation so that the output deviation from the set point is brought to zero within a reasonable number of samples. This is also called the deadbeat controller that will eliminate output error at the sampling instants in the minimum time. However, because of the time delay, this is not a reality since it would involve knowing future values of the disturbance. Hence, one chooses a controller that will minimize the variance of output. Let ^Y[subt+1] be the minimum variance forecast of the characteristic of interest at time t + 1. It can be shown that the optimal minimum variance controller is obtained by setting the control action, X[subt], such that ^Y[subt+1] = T.

A simple case of an integral controller (Figure 2) is presented here to show the application of a MMSE controller to a stochastic process. From Box, Jenkins, and Reinsel (1994) and following the notation of Montgomery (1996), we have

Y[subt+1] - T = gX[subt],

where g is the process gain for a system with drifting mean. If no adjustment is made, then the process will drift away (here we are considering a stochastic process) from the mean according to

Y[subt+1] - T = N[subt+1],

where N[subt+1] is the disturbance at time t + 1.

The disturbance often can be modeled by the ARIMA(0,1,1) model given by

^N[subt+1] = ^N[subt] + lambda(N[subt] - ^N[subt]). (1)

The ARIMA(0,1,1) model is also known as the IMA(1,1) or exponentially weighted moving average (EWMA). This model is well known for its robustness.

In terms of output Y[subt], we have

Y[subt+1] - T = N[subt+1] + gX[subt].

Since N[subt+1] is unknown at time period t, it is necessary to forecast N[subt+1] by ^N[subt+1]. Hence,

Y[subt+1] - T = e[subt+1] + ^N[subt+1] + gX[subt],

Where

e[subt+1] = N[subt+1] - ^N[subt+1].

It is a usual practice in EPC to shift the output disturbance to some other process input variable that is generally the manipulated variable (here it is X[subt]). In order to keep the system on target, the actual adjustment in terms of MMSE using integral control is calculated as

X[subt] = - (lambda/g)[Graphic Character Omitted]e[subj].

In this equation, g is the gain, e[subj] = Y[subj] - T, and lambda is the EWMA parameter.

There are situations, particularly if dynamic changes are slow compared with the sampling rate, where MMSE control gives undesirably larger variations in the input X[subt]. It is then possible to introduce a constrained controller in which the mean square error of the output deviation from target is minimized subject to a constraint on the variance of the input changes. The important feature of the constrained controller is that by allowing only a very small increase in the mean square error of the output, a very large reduction can usually be made in the variance of the input.

CASE STUDY: EXPLOSIVE POWDER STUDY

The case study presented here deals with the integration of SPC and EPC in a powder loading operation for an automobile air-bag initiator. The initiator, as the name indicates, fires the explosive charge that releases gases to expand the air bag. The explosive powder used in the initiators is prepared by mixing proper ratios of oxidizer, binder, and other oxidizing agents. The mixture is subjected to a blending operation, followed by precipitation of the binder and drying of the entire mixture. The powder processing is carried out in a closely controlled environment. The powder is sensitive to moisture and dust, and, above all, is very volatile. One variable that is not controlled is relative humidity. Relative humidity affects the powder flow and powder weight characteristics. Usually, a large volume of powder (approximately one kilogram) is prepared at a time and is dispensed into the initiator by an automated machine. The powder is placed in a vibratory bowl, and a spoon dispenses a fixed amount of powder (1 +/- 0.02 grams) into the initiator. The machine has the capability to measure the powder weight for every initiator in real time and accept or reject the part accordingly. This study involves process control of discrete part manufacturing. However, the powder used in the part is produced as continuous process. We refer to the combination of discrete part and continuous process operations as "hybrid". This case study illustrates the use of MacGregor's modified rule #2 of the funnel experiment in an effective fashion for the powder data. Our study indicates that it is not always best to leave the system alone when there is a correlated and systematic variation in the output.

X and R charts are used to monitor the average powder weight at fixed intervals. The flow properties of the powder is a function of density that in turn depends on the humidity (disturbance) and amplitude of vibration of the feeder bowl. The amount of powder in the initiator is critical for successful operation of the initiator. Too much powder will lead to delay in firing, and too little powder will lead to insufficient explosion pressure. Figure 3 is the plan view of the automated powder loading machine.

The machine was experiencing more than desirable variation in powder weight leading to excessive rejects. It also has been noticed that the powder flow characteristics were changing with time. Figure 4 shows the time-sequence plot of the powder weight, and it was evident from the figure that the mean of the powder weight appears to be drifting over time. The X and R chart (Figure 5) indicates that few points were outside the control limit. Figure 6 presents the relative humidity over a three-month period, during which it increased from 25% to 55%. The series was differenced to make it stationary (Figure 7). Then an autocorrelation plot was made of the differenced series (Figure 8). This plot suggests a moving average (MA) model of order one. Using time series analysis, the MA parameter was estimated to be 0.6. This implies that lambda of Equation (1) is 0.4. Since the parameter lambda is determined so that the mean squared errors are minimized, lambda = 0.4 yields the MMSE for this system.

The flow characteristics of the powder also depend on the amplitude of the vibrator bowl that can be adjusted on demand by the machine. Based on engineering studies, the gain in the system is set to 0.6:1, which means an increase in the amplitude by 1 unit increases the powder dispensed by 0.6 unit. Since the target is one gram,

Y[subt+1] - 1 = N[subt+1] + 0.6X[subt].

Since the disturbance model corresponds to an EWMA, we shall forecast the disturbance with EWMA having lambda = 0.4:

^N[subt+1] = 0.4N[subt] + 0.6^N[subt]

= 0.4(Y[subt] - 1) + 0.6^N[subt],

where T is the Target.

The magnitude of adjustment made to the amplitude of the vibratory bowl is given by

X[subt] - X[subt-1] = - (lambda / g) (Y[subt] - 1)

= - (2 / 3) (Y[subt] - 1).

Figure 9 shows the time sequence plot of average powder weight dispensed after adjustment is applied; from the figure it is evident that the mean powder weight has less variation and is closer to the mean value. Figure 10, the X and R charts for the powder data, does not show parts out of tolerance. The Autocorrelation Function (ACF) plot of the adjusted disturbance (Figure 11) does not reveal any structure, indicating effective use of integral control in a feed-back fashion. Figure 12 shows the adjustment made to the feeder bowl to keep the powder weight on target.

There are many concerns regarding the role of process adjustment in reducing variability. For instance, a control chart alone cannot achieve elimination of variability around a target. In the chemical and process industries, it is observed that controls such as the simple integral control can be used effectively for this purpose. In general, EPC depends on the fact that we can predict the next observation, designate a manipulatible variable in order to affect the process output, and understand the effect of that particular manipulated variable in order to determine the amount of control action required to keep the process on target.

In the above case of powder weight, the variation in the output is shifted to the manipulatible variable amplitude of vibration of the feeder bowl. We made an effective integration of SPC and EPC for this case by monitoring the powder weight disturbance and maintaining the bowl amplitude at a target value. Whenever the mean of the powder weight drifts beyond control limits, a signal was sent to the bowl mechanism to compensate for the drift in the mean powder weight.

We recommend monitoring the manipulatible variable since it will provide valuable information on the process output. In this case, such monitoring would focus attention on the powder weight variation. If the compensation provided results in large variation and exceeds preset control limits, then this may indicate that the process has encountered an assignable cause of variation (for instance, inadequate dispensing of powder due to some powder sticking to the spoon, leading to less powder dispensed to the parts), in addition to the built-in correlation of the output variable.

Figure 13 provides a pictorial illustration of the integration of SPC and EPC for powder weight process control.

CONCLUSION

The case study presented here indicates a clear application of integration of SPC and EPC for process monitoring and control for parts/hybrid industries. The study also shows effective application of SPC/EPC integration in order to achieve the desired goal. An overview of SPC, EPC and integration issues have been discussed The authors strongly recommend further research, such as constrained MMSE control (in certain situations, MMSE control requires unacceptably large manipulations that may be beyond the scope of adjustment) and multivariate control. This paper demonstrates that SPC, already used for process monitoring in the parts industries, and EPC, now used in process industries, may be integrated in a hybrid industry for more effective control of processes.

Added materialADDED MATERIAL

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ACKNOWLEDGMENTS

We wish to thank a referee for many helpful suggestions which have been incorporated into this version of our study.

TABLE 1. SPC and EPC Comparison (Messina (1992))

	SPC	EPC
Philosophy	Minimize variability by detection of and removal of process upsets.	Minimize variability by adjustment of process to counteract process upsets.
Application	Expectation of process stationarity.	Expectation of continuous process drift.
Deployment:		
Level	Strategic	Tactical
Target	Quality Characteristics	Process Parameters
Function	Detecting Disturbances	Monitoring Set Points
Cost	Large	Negligible
Focus	People and Methods	Equipment
Correlation	None	Low to High
Results	Process Improvement	Process Optimization

FIGURE 1. Relationship Between EPC and SPC (Montgomery (1996)).

FIGURE 2. An Integral Control Process With Pure Gain.

FIGURE 3. A View of Ignition Powder-Loader.

FIGURE 4. Time Sequence Plot of Powder Weight.

FIGURE 5. X and R Chart for Powder Weight.

FIGURE 6. Relative Humidity Over a Three Month Period.

FIGURE 7. Differenced Relative Humidity Series.

FIGURE 8. Autocorrelation Function of the Differenced Relative Humidity Series.

FIGURE 9. Time Sequence Plot of Powder Weight.

FIGURE 10. X and R Chart for Powder Weight.

FIGURE 11. ACF of Disturbance With SPC/EPC.

FIGURE 12. Time Sequence Plot of Bowl Vibration.

FIGURE 13. Powder Dispensing Study.

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Source: Journal of Quality Technology, Jul98, Vol. 30 Issue 3, p189, 12p
Item: 781274