Integration of Multivariate Statistical Process Control and Engineering Process Control

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Abstract

Two independent methods for improving quality are engineering process control (EPC) and statistical process control (SPC). The first method tries to minimize variability by handling process variables so as to keep the outputs of the process on target. While the latter method, SPC does the same basic task of minimizing variability by supervising and eradicating the assignable causes of variation. This paper compares EPC working alone with integrated use of EPC and SPC for multivariate cases. Simulations are performed to evaluate the average of performance measures. Simulations results indicate that MEPC and MPSC combination performs better than using either of them individually. Furthermore, two different schemes of integration are discussed and evaluated namely application of SPC on the output and input of the process. It is concluded by the simulations that application of both of them simultaneously is better, in general, than using either of them alone.

Keywords
Multivariate Statistical Process Control, Multivariate Engineering Process Control, Integration of multivariate engineering process control and multivariate statistical process control.

1. Introduction

Statistical Process Control (SPC) and Engineering Process Control (EPC or sometimes called as Automatic Process Control APC) are two techniques that are used for improving process productivity and product quality by reducing the variability of process from target while keeping it stable and under control. Statistical process control, a widely used technique, accomplishes the above mentioned task by monitoring and tracking major changes in the behaviour of a system. It is an effective monitoring technique as far as the process variables can be stated by independently observed statistical variables whose values fall in the vicinity of deterministic values. On the contrary, engineering process control is a continuous procedure that adjusts the process manipulatable variable in order to keep the output on set point or target. (Box and Kramer 1992) described the historical aspect of these techniques by mentioning that the Statistical Process Control has its roots in the parts industry or discrete manufacturing whereas, Engineering Process Control originates from the process industry.

Let us consider a daily life example to understand the basic principles of statistical process control, engineering process control and the need to integrate them. Let us consider a room (system/process in EPC terminology) having output as the room temperature. If Statistical Process Controller were to control the output i.e. temperature, it would look for the notable deviation from the target value and turn on the fan or AC whenever the temperature falls outside the limit; however, the fan or AC shall be switched off as soon as the value of the temperature returns back within the prescribed limit. Evidently this is not the desired behaviour of the system.

On the other hand the Engineering Process Control shall continuously monitor the deviation of temperature from the target and adjust the fan or AC speed (process manipulatable input) accordingly to keep the process output on target. Now the system is under the desired controlled state. However, one can imagine a condition where a fault/assignable cause occurs in the system, for instance, a leakage in air duct or an obstacle sticking in flow of cool air etc. Engineering Process Control can fail here by increasing the speed of AC or fan in order to compensate for the deviation in the output i.e. the room temperature caused by the fault or assignable cause. In this kind of scenarios, the need to integrate both techniques arises. In an integrated system considering our example, EPC shall take care for the normal operation whereas, SPC shall detect the assignable cause (leakage etc.) and eliminate the cause by repairing the fault instead of wasting energy by the AC or fan.

Integration of Statistical Process Control and Engineering Process Control got first attention in 1988 when (MacGregor 1988, Box and Kramer 1992) proposed this concept of integration and convinced the SPC research community that control charts can be used to monitor a "controlled" system. He reviewed the two schemes, their similarities, overlap, contradictions, reasons behind their isolation and the need to integrate them. (Montgomery and Keats 1994) formulated the model for integration using Shewart and CUSUM control charts as monitoring tools and added the minimum mean squared error (MMSE) EPC rule in further work whereas (Montgomery and Keats 1994) were also among initiators who started to develop this integration technique.

All of the above researches suggested that combined application of both EPC and SPC can outclass the application of either of them alone in most of the cases. The fundamental work of the above mentioned researchers was followed by many others that can be broadly classified into two categories based on the integration approach.

SPC triggered EPC

One of the popular schemes of SPC/EPC integration involves triggering of EPC controller only in case when SPC signals presence of assignable cause or out-of-control signal; (Nembhard and Mastrangelo 1998) were the earliest of many in this horizon who have advocated that EPC based process adjustments should only be triggered if SPC detects the out-of-control state of the system. (Jiang and Tsui 2000) provided a concept similar to that of (Nembhard and Mastrangelo 1998) by suggesting a cost based model in which the EPC adjustments were only supposed to be triggered through an out-of-control signal provided by SPC based monitoring. They only considered the out-of-control and in-control costs and made a handful of assumptions to simplify the problem. A contrary approach is to continuously use EPC for controlling and process adjustment while using SPC for detection of assignable cause by monitoring output or input variables of the process. Applying EPC continuously implies to loss of resources, whereas EPC only triggered by SPC in out-of-control condition amounts for loss of quality. Therefore, (Duffuaa *et al.* 2004) proposed a scheme that takes short comings of both the approaches into consideration and propose an integrated scheme comprising Taguchi's Quality Engineering. In the mentioned approach SPC plays dual role; apart from being used to search for assignable cause, it also provides required quantities to a TQL function that estimates the cost of associated quality loss. Meanwhile, the cost of EPC implementation for the same instant is also calculated. Finally, EPC is only allowed process adjustments when cost of adjustment is less than the cost of quality loss.

Integration for assignable cause detection:

The most powerful approach of SPC and EPC integration involves continuous adjustments using EPC and detection of assignable cause using SPC monitoring. Several researchers have explored different EPC techniques along with different control charts for this purpose. Shewart, Exponentially Weighted Moving Average (EWMA) and Cumulative Sum (CUSUM) control charts were used in integrated models before (Shao 1998) introduced Cumulative Score (CUSCORE) control charts as SPC tools in the arena of EPC/SPC integration. Furthermore, (Shao and Chiu 1999) formulated a graphical aid technique meant to recognize the type of disturbance or assignable cause (either shift in mean or a drift). Later on (Shao *et al.* 1999) demonstrated an adaptive controller technique that is triggered by SPC based assignable cause detection and aims at identifying the changing parameters of the disturbance and consequently adjusting the process until the underlying cause is completely eliminated. Process subjected to a slowly changing trend was considered by (Xie *et al.* 2001). It is a special case of SPC and EPC integration in which it is insufficient to only monitor the process that changes with time using SPC. Accordingly a model had been developed that makes adjustment to the process after regular intervals of time and the process output itself is monitored with changing control limits instead of its variation from the target value. SPC/EPC integration for univariate case was comprehensively discussed by (Huang and Lin 2002) and the associated issues had been addressed. In the mentioned study, effects of Shewart and CUSUM control charts on an MMSE regulated system with shifting and drifting mean disturbances had been taken into account. (Huang and Lin 2002) noted that Shewart control charts are more effective than CUSUM control charts in detecting the shifts. In case of drifting disturbance with smaller slope, CUSUM proves to be more effective where as for larger slopes Shewart is more efficient. Moreover, it was noted that an EPC feedback compensation mechanism affects SPC out-of-control detection and disturbs the output when suddenly assignable cause is removed. To account for this so called overcompensation issue, a joint monitoring scheme of Shewart and CUSUM charts had been used to recognize the disturbance type and a cost based decision rule is provided to decide whether the assignable cause removal will be cost efficient owing to the fact that the overcompensation phenomenon is irresolvable and in some cases renders the system unstable.

All of the before mentioned discussions were confined to SISO systems i.e. single input-single output systems. On the contrary, numerous manufacturing processes, for instance, paper manufacturing process, power generation process, oil separation process and silicon epitaxy process are MIMO processes i.e. multiple input-multiple output processes. Therefore, for practical purposes there is a demand for the integration of MEPC and MSPC. Although (Yang and Sheu 2005, 2007), (Raich and Çinar 1996), (Tong *et al.* n.d.) and (Jiang *et al.* 2008) have proposed certain schemes for integration of multivariate cases and some others have applied PCA, PLS and other Fault Detection techniques to interpret noises and variations in the multivariate process, there remains a necessity of further research in this vast area.

This paper is meant to elaborate the usefulness of integrating SPC and EPC for the multivariate cases, propose a novel scheme of integration and discuss its effectiveness using a numerical example. The subsequent section of this paper discusses the novel scheme developed herein for integration of multivariate statistical process control and engineering process control. Section 3 describes model of the system and multivariate engineering process controller used in this work. It is followed by a brief introduction of the statistical process control technique used in this paper. Section 5 covers demonstration of the idea using a simple numerical example. Lastly, sensitivity analysis justifies the use of proposed integration scheme.

2. An Integrated SPC/EPC MIMO Control System

In light of the above mentioned literature survey, an integrated control system model has been proposed here. It is well established in the literature that applying control charts on process output yield to detection of assignable causes. Hotelling's $\chi 2$ Chart is the simplest and the most fundamental control chart meant to monitor a system already being regulated by EPC scheme. A short coming in applying Hotelling's $\chi 2$ Chart to process output is its inability to detect assignable causes that appear small in magnitude on output; for instance, a mean shift in noise culminating the output. The popular solution to this problem is the use of rather complex control charts such as EWMA, CUSCORE or GWMA control charts. (Tsung and Kwok-leung 2003) investigated a rather unique approach i.e. to apply control charts on process inputs instead of output. Inspired by (Tsung and Kwok-leung 2003) and other researchers, we adopt a "Joint Monitoring" of process inputs and outputs in order to detect the assignable cause in MIMO systems. As it is argued in the subsequent sections, the proposed method is the best way to detect assignable causes of broader ranges. This eliminates the need for using complex control charts relieving engineers, who have seldom in-depth knowledge of statistical techniques, from designing control charts. The proposed MIMO control system is illustrated by the following block diagram:

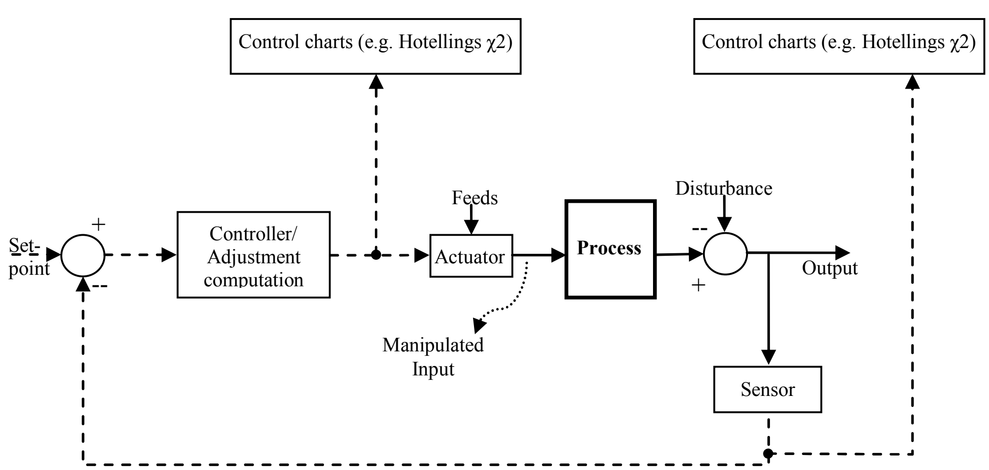

Figure 1: Block diagram of the proposed control system

In the figure, the process is illustrated by a bold block that is fed through actuator(s); data flow and material flow are represented by dashed and solid lines respectively. As it is clear from the figure, the output is measured by sensor(s) and the measured value(s) are subtracted from the set-point or target values in order to generate the error. This error is used in the controller block that performs mathematical calculations based on the amount of error and the plant mathematical model in order to adjust or manipulate the process input through actuator(s). In the proposed scheme, the multivariate SPC control charts (generally Hotelling's $\chi 2$ will be enough) are employed both at process inputs and outputs for detecting assignable causes of variation. Following sections discuss application of the proposed scheme using a simple system and shed light on its effectiveness under different situations.

3. System Description and MEPC Scheme

Ingolfsson and Sachs [11] targeted the process control problem and discussed the conditions for the stability of a process using a single EWMA (exponentially weighted moving average) controller having taken into account a first-order process/system. (Butler and Stefani 1994) introduced a double EWMA controller and found it useful in eradicating the deterministic drift within the process. Furthermore, Tseng et al. suggested a multivariate EWMA controller for a linear multi-input and output model. (Castillo and Rajagopal 2002) proposed an MIMO double EWMA feedback controller for drifting processes.

For MEPC scheme, (Yang and Sheu 2005) consider a linear MIMO system with *m* inputs and *p* outputs after Tseng et al. [11], described by the following equation:

$$y_i = \alpha + \beta c_{i-1} + \varepsilon_i \tag{1}$$

where, y_i is a vector of dimensions (p×1) comprising the outputs, α is a (p×1) vector containing the offset parameters of each output, β is a process gain matrix having p rows and m columns, c_{i-1} is an (m ×1) vector comprising the values of manipulatable inputs, and ε_i is a (p×1) vector denoting the noise or process disturbance. ε_i is assumed to be contributing in the dynamics of the system.

The offset in the output or the intercept will be updated online after each iteration. For simplicity we shall assume that the estimate of β denoted by B is known. Let $\acute{\alpha}_0$ denote the estimate of α at i = 0, then the predicted model will be:

$$\hat{y}_i = \hat{\alpha}_0 + B c_{i-1} \tag{1a}$$

Prior to implementation of the feedback control scheme, the process (manipulatable) input will look like:

$$c = B^{-1}(\tau - \hat{\alpha}_0) \tag{2}$$

where τ is the target vector. Multivariate EWMA controller proposed by Yang and Sheu [19] is described by the following equation:

$$\hat{\alpha}_i = \hat{\alpha}_{i-1} + \omega(y_i - \tau) \tag{3}$$

where ω is a discount factor. Now, for the i_{th} iteration, c_i can be described as follows :

$$c_i = (I - B^T(BB^T)^{-1}B)c_{i-1} + B^T(BB^T)^{-1}(\tau - \hat{\alpha}_0) \tag{4}$$

Let $\alpha_0 = 0$ and $\tau = 0$; then, the off-target amount at iteration i can be described as :

$$y_i - \tau = y_i$$
$$y_i = (1-\omega)^{i-1} y_0 + \sum_{t=0}^{i}(1-\omega)^t(\varepsilon_{i-t} - \varepsilon_{i-t-1}) \tag{4b}$$

When the ε_i is a white noise with mean vector μ and variance Σ, the covariance of y_i will be:

$$\Sigma_{yi} = \left(1 + \frac{\omega}{2-\omega}\left(1 - (1-\omega)^{2(i-1)}\right)\right)\Sigma \tag{5}$$

It is considered in control action of Equation 3, taken by EWMA controller, that assignable cause doesn't exist. Therefore, the only source of common cause of disturbance is a white noise series ε_i that is described by Equation 1. Now, the performance of this system is investigated under additional assignable causes. Let us consider that that this MIMO process model is generally controlled by MEPC and that the MSPC monitoring scheme will only report assignable causes i.e. external changes. Assignable causes can be rapidly detected by application of MSPC control charts to the deviation of output from target; it's considered that the assignable cause takes the form of a sustained shift in the process mean vector. The output deviation will obviously reduce upon successful detection and eradication of external changes or assignable causes. Firstly, in this paper, using MEPC scheme alone is compared with using MSPC together with MEPC. Concerning this, Hotelling's χ2, the MEWMA and the MGWMA control charts have been used for monitoring the output deviation from the target. Secondly, two different integration schemes are compared: Applying MSPC to process output and to process input. Only Hotelling's χ2 chart has been used for this purpose.

4. Hotelling's χ2 Chart

A counter part of univariate Shewhart $\bar{X}$ is Hotelling's $\chi 2$ control chart; it's used to monitor the process mean vector. As per the multi input multi output system established in Sect. III, let us consider a white noise series $\boldsymbol{\varepsilon} i$ (used in Equation 1) be independent multivariate normal random vectors with mean vectors $\boldsymbol{\mu}_i$ and a common covariance matrix $\sum$, which is non-singular. The covariance matrix of $\mathbf{y}_i$ (denoted by $\sum_{\mathrm{y}i}$), that is given by the Equation 5, is calculated by measuring the deviations of $\mathbf{y}_i$ from the target vector ($\tau = 0$). Moreover, an out-of-control condition is signalled by Hotelling's $\chi 2$ control chart as soon as the statistic T_i^2,

$$T_i^2 = y_i' \textstyle\sum_{yi}^{-1} y_i \qquad (6)$$

exceed the UCL at iteration i, where UCL (h1) is selected so as to achieve desired ARL. For detailed discussion on Hotelling's charts (Hotelling 1947, Montgomery 2007) can be referred.

5. A Numerical Example

In this example a simple case of 2 variables has been taken into account to elaborate the idea of integration of MEPC and MSPC. Two integration schemes have been demonstrated using this example. The first scheme i.e. application of MSPC on the output has been elaborated using four control charts whereas the second scheme i.e. application of MSPC on the process input has been briefly illustrated using one control chart. However, subsequent section considers sensitivity analysis for establishing that both of the techniques are effective in contrasting scenarios.

For simplicity the example considered by Yang and Sheu[19] is taken into account here as well. Let the number of production runs n = 100. The mean vector of $\boldsymbol{\varepsilon} i$ is assumed to be on target at [0 0]' for the first 20 observations where the white noise series $\boldsymbol{\varepsilon} i$ in Equation 1 follows the bivariate normal distribution. A disturbance of the form of shift having mean vector [0.875 0]' is introduced into the process at time i = 21 i.e.

$$\mu_0 = [0\ 0]', \mu_1 = [0.875\ 0]'$$

Let ω = 0.1 and

$$\hat{\alpha}_0 = [1\ 1]', B = \begin{bmatrix} 1 & 0 \\ 1 & 0 \end{bmatrix} \Sigma = \begin{bmatrix} 1.0 & 0.5 \\ 0.5 & 1.0 \end{bmatrix} \gamma_0 = [0.2\ 0.2]'$$

From Equation 2, we get

$$\tau_0 = [-1 - 1]'$$

For the simulation of this example, Mathwork's Matlab has been used. The white noise vector has been generated by the built-in command of Matlab.

Output observations of the MIMO model described by Equation 1 during 100 iterations are illustrated by Figure 1 where only MEWMA controller (given by Equation 3 and 4) is applied. A disturbance of the form of shift having mean vector [0.875 0]' is introduced into the process at time i = 21. Figure 3 illustrates the control actions of Equation 4. In the absence of MSPC control charts meant to detect the shift, the control action produced by MEWMA controller ($c1$) increases to a very large extent in order to compensate for this sustained shift.

The statistics of T^2_i have been illustrated in figures 4 for the case in which a Hotelling's χ2 chart is applied to the deviation of outputs from the target in addition to the MEPC rule. Corresponding values of T^2_i for Hotelling's χ2 chart have been calculated using Equation 6. The calculations of (Yang and Sheu 2005) have been adapted in order to insure ARL_0's of 200; therefore, the control limit is $h1$ = 9.2.

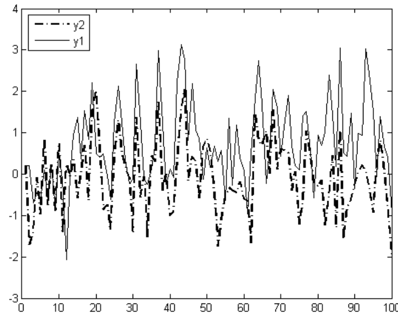

Figure 2: Output fluctuation of the process employing only MEPC. A shift of mean vector [0.875 0]' is introduced at i = 21.

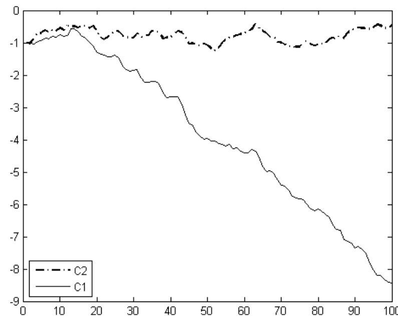

Figure 3: Control actions for the process when only MEPC scheme has been applied. A shift of mean vector [0.875, 0]' is introduced at 21st iteration.

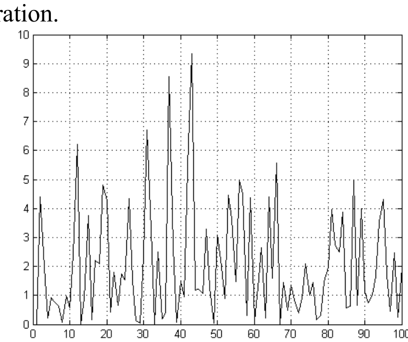

Figure 4: T_i^2 statistics after joint application of MEPC and a Hotelling's $\chi 2$ chart. A shift of mean vector [0.875, 0]' is introduced at 21st iteration.

Now let us consider the case of applying MSPC on the process input along with MEPC. Hotelling's $\chi 2$ control chart is applied on input in the same example. Since the mean and covariance vectors of input are unknown, the Hotelling's $\chi 2$ chart is implemented after at least 5 iterations have taken place under MEPC only. Once enough samples are available, the mean and covariance vectors are determined using Matlab built-in commands. The UCL of the chart (h4 = 10.0) is adjusted for ARL_0=200 using as many as 500 simulations. Using MSPC at input, it was observed that the shift was detected on 38^{th} iteration and the performance measure was 1.2292 in contrast with the detection on 41^{st} iteration and performance measure of 1.2590. The graph of input variations has been shown in figure 9. It is evident from the figure that this method is more prone to false detection when compared with figures 3, 4 and 5.

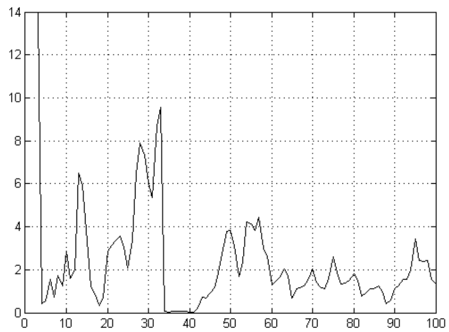

Figure 5: Application of MSPC on input recipes

Findings, using above example, suggest that applying MSPC at input has an edge over applying MSPC on output; however, it needs to be verified for different magnitudes of shifts. The following section discusses the idea in more detail.

6 Sensitivity Analysis

For comparison of the two schemes developed in previous section, a detailed and general case analysis is considered here. An assignable cause of the form of sustained shift is considered. The shift magnitudes of 0.25, 0.5, 1, 2 and 5 are investigated. Hotelling's $\chi 2$ control chart is applied on both output and input of the process one by one. An in-control (zero shift) ARL (ARL_0) is maintained at approximately 200 by changing the width of the control limits. For each case, 500 simulations were run, whereas, 200 iterations were done in each simulation. A sustained shift is introduced on 21^{st} iteration in each simulation run and it's assumed that the assignable cause (sustained shift) is removed as soon as it is detected. The out-of-control ARLs (ARL_1s) and performance measures (Euclidean average) are compared for both the schemes. Both ARL_1s and PMs are averaged for 500 simulation runs where each simulation run comprises 200 iterations. Summary of these simulations performed using Matlab is illustrated in Table 1. In Table 1, first column shows the shift magnitude that was introduced in the output of the process. The subsequent columns display the ARL_1s and PMs when Hotelling's $\chi 2$ control chart is applied on output/input of the process. When applied on output, Hotelling's $\chi 2$ chart detects shift faster than its application at input when the shift magnitude is higher. However, the trend inverses down the table where shift magnitude is reduced. Furthermore, PMs of first scheme under larger shifts is better while the PMs of second are better for smaller shifts.

Table 1: Comparison of ARLs and PMs when MSPC is applied at Output and Input

Shift Magnitude	Hotelling's $\chi 2$ chart at Output h1 = 9.2 for ARL_0 =200		Hotelling's $\chi 2$ chart at Input h1 =10.1 for ARL_0 =200	
	ARL_1	PM	ARL_1	PM
5	1.02	1.2699	17.10	1.2904
2	3.92	1.2771	18.83	1.2786
1	23.02	1.2937	36.07	1.2778
0.75	60.58	1.2843	46.34	1.2621
0.5	128.90	1.2731	59.38	1.2528
0.25	183.30	1.2521	92.30	1.2513

Therefore, application of Hotelling's $\chi 2$ control chart on output is more effective than its application on input when the shift magnitude is higher; whereas, for smaller shift magnitudes, application of Hotelling's $\chi 2$ control chart on input shows better results than its application at output. This finding is evident from both ARL_1s and performance measures. Hence, simultaneous application of both the schemes is recommended for general cases.

7 Conclusion

Multivariate Statistical Process Control and Engineering Process Control are two complementary techniques used in the area of process control. EPC tries to minimize the deviation of process from target, or in other words, prevents the effect of disturbance (common causes of variation) by manipulating process input. On the contrary, SPC aims at monitoring the process for assignable causes of variation, detects them and ultimately eliminate them as soon as possible. Various schemes of integration between SPC and EPC had been proposed in literature with a view to complement each others' shortcomings.

A novel scheme of integration has been proposed and evaluated in this paper considering Multiple-Input-Multiple-Output (MIMO) systems. A numerical example has been presented in order to explain the idea behind integration of the two complementary schemes. Furthermore, it has been established in this work that joint monitoring of an EPC regulated process' outputs and inputs using SPC leads to the earliest detection of assignable causes. Sensitivity analysis has been performed to ensure that the findings hold in different scenarios of assignable causes.

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Biography

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