Quality Technology & Quantitative Management
Vol. 4, No. 3, pp. 345-363, 2007

QTQM
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Integrating SPC and EPC Methods for Quality Improvement

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(*Received* May 2005, *accepted* February 2006)

Abstract: Process variations are classified into common cause and assignable cause variations in the manufacturing and services industries. Common cause variations are inherent in a process and can be described implicitly or explicitly by stochastic methods. Assignable cause variations are unexpected and unpredictable and can occur before the commencement of any special events. Reducing process variations are critical for industries with a low tolerance for variability such as semiconductor manufacturing. While engineering process control (EPC) methods such as feedback/feedforward controllers are widely employed in continuous process industry to reduce common cause variations, statistical process control (SPC) methods have been successfully utilized in discrete parts industry through identification and elimination of the assignable cause of variations. Recently, integration of EPC and SPC methods has emerged in the semiconductor manufacturing industry and has resulted reducing manufacturing waste and improving process efficiency. This paper provides a review of various control techniques and develops a unified framework to model the relationships among these well-known methods in EPC, SPC, and integrated EPC/SPC. A case study centered on chemical mechanical planarization process demonstrates the utility of this framework.

Keywords: Automatic process control, chemical mechanical planarization, control charts, run-to-run control, semiconductor manufacturing.

1. Introduction

Two categories of research and applications have been developed independently to achieve process control. Engineering process control (EPC) uses measurements to prescribe changes and *adjust* the process inputs intended to bring the process outputs closer to targets. By using feedback/feedforward controllers for process regulation, EPC has gained a lot of popularity in continuous process industries. Statistical process control (SPC), on the other hand, uses measurements to *monitor* a process and look for major changes in order to eliminate the root causes of the changes. Statistical process control has found widespread applications in the manufacturing of discrete parts industries for process improvement, process parameter estimation, and process capability determination. Industries such as hospital service, business marketing and financial management have also embraced SPC for detecting important process changes to support decision making and improving quality.

Practitioners of SPC argue that because of the complexity of most manufacturing processes, EPC methods can over-control a process and increase process variability before decreasing it as demonstrated by Deming's funnel experiment (Deming [24]). Moreover, important quality events may be masked by frequent adjustments and become difficult to be detected and removed. Conversely, practitioners of EPC criticize SPC methods as being

exclusive of the opportunities for reducing the variability in the process output. Due to the stochastic nature of manufacturing processes, traditional SPC methods generate many false alarms and fail to discriminate quality deterioration from the in-control state defined by SPC rules. Recently EPC and SPC has been integrated in the semiconductor manufacturing and resulted in a tremendous improvement of industrial efficiency (Sachs *et al.* [49]).

The integration of EPC and SPC techniques employs an EPC control rule to regulate the system and superimposes SPC charts on the EPC controlled system to detect process departures from the system model. Both academic research and industrial practice have shown the effectiveness of the EPC/SPC integration model when the process is subjected to both systematic variations and special cause variations (Montgomery *et al.* [39]; Capilla *et al.* [16]; Jiang and Tsui [27]). To avoid confusion, Box and Luceno [13] refer to EPC activities as *process adjustment* and SPC activities as *process monitoring*. While the two approaches have been applied independently in different areas for decades, the relationship between them has not been clearly explored yet.

Section 2 of this paper reviews various SPC and EPC techniques for industrial process control. Section 3 presents the integrated model of EPC/SPC. Section 4 reviews several cutting-edge statistical process control methods for monitoring autocorrelated and EPC processes. Section 5 presents a case study of a chemical mechanical planarization (CMP) process to demonstrate the utility of the EPC/SPC method. Section 6 discusses design issues for EPC/SPC systems. Section 7 presents some concluding remarks.

2. Two Process Control Approaches

2.1. Engineering Process Control

Engineering process control is a popular strategy for process optimization and improvement. It describes the manufacturing or information manipulation process as an input-output system where the input variables (recipes) can be manipulated (or adjusted) to counteract the uncontrollable disturbances to maintain the process target. The output of the process can be measurements of the final product or critical in-process variables that need to be controlled. In general, without any control actions (adjustment of inputs), the output may shift or drift away from the desired quality target due to disturbances (Box and Luceno [13]). These disturbances are usually not white noise but usually exhibit a dependence on past values. Thus, it is possible to anticipate the process behavior based on past observations and to control the process and outputs by adjusting the input variables.

As the name implies, EPC requires a process model. A simple but useful process model that describes a linear relationship between process inputs and outputs is (Vander Wiel *et al.* [58]),

$$e_t = gX_{t-1} + D_t \tag{1}$$

where e_t and X_t represent the process output and input (control) deviations from target, D_t represents the process disturbances which pass through part of the system and continue to affect the output, and g is the process gain that measures the impact of input control to process outputs. To simplify our discussion, we assume that the process gain is unity, i.e., $g = -1$. When no process control is involved, the process output is simply the disturbance, and the variance of the output is obtained as σ_D^2. The objective of process control is to reduce process variations by adjusting inputs at the beginning of each run, *i.e*, $\sigma_e^2 < \sigma_D^2$, where σ_e^2 is the variance of the controlled output.

Feedforward control uses prediction of the disturbance to adjust the process,

i.e., $X_{t-1} = \hat{D}_t$, where $\hat{D}_t$ is the prediction of disturbance at time t given process information up to $t-1$. It strongly relies on an accurate sensor and measurement system to capture the process disturbance. Another process control strategy widely adopted in industry is feedback control, which uses deviations of the output from the target (set-point) to indicate that a disturbance has upset the process and calculate the amount of adjustment. Figure 1 presents a typical process with a feedback control scheme. Since deviations or errors are used to compensate for the disturbance, the compensation scheme is essentially two-fold. It is not perfect in maintaining the process on target since any corrective action is taken only when the process deviates from its target first. On the other hand, as soon as the process output deviates from the target, corrective action is initiated regardless of the source and type of disturbances. It is important to note that feedback scheme is beneficial only if there is autocorrelations among the outputs.

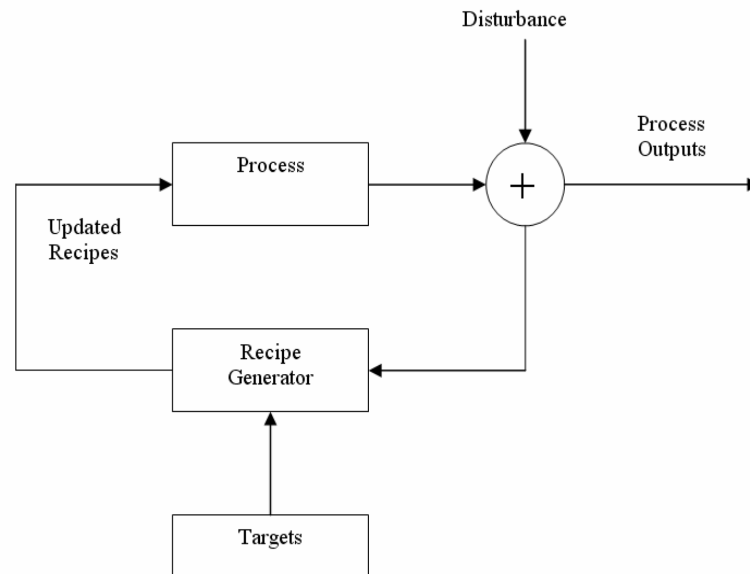

Figure 1. A feedback controlled process.

There is a rich body of research on feedback controllers (Astrom and Wittenmark [8]). To minimize the variance of the output deviations from the quality target, two types of controllers are popularly used.

- Minimum Mean Square Error (MMSE) Control. From the time series transfer function model that represents the relationship between the input X_t and output e_t, Box *et al.* [11] develop the MMSE controller

$$X_t = -\frac{L_1(B)L_3(B)}{L_2(B)L_4(B)} e_t$$

where B is backshift operator, $L_1(B)$, $L_2(B)$, $L_3(B)$ and $L_4(B)$ are polynomials in B which are relevant to the process parameters. Theoretically, if the process can be accurately estimated, the output can be reduced to a white noise by the MMSE controller.

- Proportional Integral Derivative (PID) Control. It is a special class of the Autoregressive Integrated Moving Average (ARIMA) control model. The three mode

PID controller equation is formed by summing three methods of control, proportional (P), integral (I), and derivative (D). The discrete version of the PID controller is

$$X_t = k_0 + k_P e_t + k_I \sum_{i=0}^{\infty} e_{t-i} + k_D (e_t - e_{t-1}) \quad (2)$$

where k_0 is always set to zero. The proportional control action is intuitive but is not able to eliminate steady-state errors, i.e., an offset will exist after a set-point change or a sustained load disturbance. The integral control action is often used because it can eliminate offset through continuously adjusting the controller output until the error reaches zero. The function of the derivative control action is to anticipate the future behavior of the error signal by considering its rate of change (Seborg *et al.* [50]). Tsung *et al.* [56] discuss design of PID controllers when the disturbance follows an ARIMA(1,1,1) model. Generally, other rules of thumb have to be used for designing a PID controller (Ziegler and Nichols [67]; Astrom and Hagglund [7]).

The MMSE control is optimal in terms of minimizing mean squared residual errors. However, this is only true for the idealized situation in which the model and model parameters are known exactly. Because the process model is not known precisely, it has a serious robustness problem when the model is close to nonstationarity. As shown in Tsung *et al.* [56] and Luceno [35], the PID controller is very efficient and also robust against nonstationarity due to the fact that it can continuously adjust the process whenever there is an offset.

Theoretically, only predictable deviations can be quantified by EPC methods. Modeling errors due to process changes are generally hard to be captured in real-time and compensated for by EPC schemes. Various adaptive EPC schemes which dynamically adjusted control parameters have been investigated. Recently, an adaptive framework is proposed in semiconductor manufacturing by superimposing an SPC scheme to monitor modeling errors and revise the process models (Sachs *et al.* [49]).

2.2. Statistical Process Control

The basic idea in SPC is a binary view of the state of a process, i.e., either it is running satisfactorily or not. As developed by Shewhart [51], the two states are classified as common cause of variations and assignable/ special cause of variations, respectively.

- Common Cause Variations. Common cause of variations is the basic assumption on which the SPC methods are based. It assumes that the sample comes from a *known* probability distribution, and the process is classified as "statistically" in-control. In other words, "the future behavior can be predicted within probability limits determined by the common-cause system" (Box and Kramer [12]). This kind of variations, from a management point of view, is inherent in the process, and is impossible or hard to be eliminated.

- Special Cause Variations. Based on Shewhart's classification, Deming [23] argues the special cause of variations as "something special, not part of the system of common causes", should be identified and removed from the root. That is, the process output should be consistent with the postulated stable behavior or the common-cause model when the process is statistically in-control, and whenever any deviation occurs from the common cause model, one should look for and try to eliminate it.

Statistical control charts essentially mimic a sequential hypothesis test to discriminate special cause of variations from the common-cause variation model. For example, a basic mathematical model behind monitoring process mean changes is

$$e_t = \eta_t + X_t \tag{3}$$

where e_t is the measurement of the process variable at time t, and η_t is the process mean at that time. Here, X_t represents variations from the common cause system and is inherent in the process. In some applications, X_t is or can be treated as an independently and identically distributed (i.i.d.) process.

In many industrial applications, the process mean is often subject to occasional abrupt changes, i.e.

$$\eta_t = \eta + \mu_t \tag{4}$$

where η is the mean target, and μ_t is zero for $t < t_0$ and has nonzero values for $t \geq t_0$. For example, if the special cause is a step-like change, μ_t is a constant μ after t_0. When a drift is present, the process mean may follow a linear trend. The goal of SPC charts is to detect the change point t_0 as quickly as possible so that corrective actions can be taken before quality deteriorates and defective units are produced. Among many others, the Shewhart chart, the exponentially weighted moving average (EWMA) chart, and the cumulative sum (CUSUM) chart are three important and widely used control charts.

- Shewhart Chart. Process observations are tested against control limits $|e_t| > L \cdot \sigma_e$, where σ_e is the standard deviation of the chart statistic estimated by moving range and sample standard deviation. L is pre-specified to maintain particular probability properties.

- EWMA Chart. Roberts [47] proposes to monitor the EWMA statistic of the process observations, $Z_t = \sum_{i=0}^{\infty} w_i e_{t-i}$, where $w_i = \lambda(1-\lambda)^i$ ($0 < \lambda \leq 1$). The EWMA statistic utilizes past information with the discount factor (1–λ) and includes the Shewhart chart as a special case when λ=1. It has a recursive form

$$Z_t = (1-\lambda)Z_{t-1} + \lambda e_t \tag{5}$$

where Z_0 is zero or the process mean. The stopping rule of the EWMA chart is $|Z_t| > L \cdot \sigma_Z$.

- CUSUM Chart. Page [41] introduces the Cumulative Sum (CUSUM) chart as a sequential probability test, which can also be obtained by letting λ approach 0 in equation (5), *i.e.*, the CUSUM algorithm assigns equal weights to past observations. The tabular form of a CUSUM chart consists of two quantities,

$$Z_t^+ = \max[0, e_t + Z_{t-1}^+ - K], \quad Z_t^- = \min[0, -e_t + Z_{t-1}^- - K] \tag{6}$$

where $Z_0^+ = Z_0^- = 0$.

Although the purpose of these procedures is to detect process changes, we know that they may signal problems even when the process remains on target due to the randomness of observations. The expected length of period between two successive false alarms is called *in-control* average run length ARL_0. When a special cause presents, the expected period before a signal is triggered is called *out-of-control* average run length ARL_1. A control chart is desired with a shorter ARL_1 but longer ARL_0. In practice, the Shewhart chart is

sensitive in detecting large shifts while the EWMA and CUSUM charts are sensitive to small shifts (Lucas and Saccucci [34]).

In typical applications of SPC charts, a fundamental assumption is that the common cause variation is free of serial correlation. Unfortunately, the assumption of independence is often invalid in many manufacturing processes. For example, in discrete parts industry, the development of sensing and measurement technology has made it possible to measure critical dimensions on every unit produced, and in continuous process industry, the presence of inertial elements, such as tanks, reactors, and recycle streams, results in significant serial correlation in measurement variables. Serial correlations call for EPC techniques to reduce variations and put forward new challenges and opportunities to SPC for quality improvement.

3. Integration of EPS/ SPC Run-to-Run (R2R) Control

EPC and SPC are two complementary strategies developed that are often practiced in different industries for quality assurance. There is an implicit relationship between them through prediction. For example, consider a pure-gain dynamic feedback-controlled process described by

$$e_t = X_{t-1} + D_t . \tag{7}$$

Suppose $\hat{D}_{t+1}$ is an estimator (i.e., prediction) of D_{t+1} at time t, a realizable form of control could be obtained by setting $X_t = -\hat{D}_{t+1}$ and the output error at time $t+1$ becomes $e_{t+1} = D_{t+1} - \hat{D}_{t+1}$, which equals the "prediction error". For example, when the process can be described using an ARIMA model, the MMSE control has an identical form as the MMSE predictor (Box *et al.* [11]). Similarly, as discussed in Section 4, forecast-based special cause chart (SCC) essentially monitors the MMSE prediction errors of an autocorrelated process.

As an alternative, the exponentially weighted moving average (EWMA) predictor, which corresponds to the integral (I) control, is one of the most frequently used prediction methods in business and industry mainly due to its simplicity and efficiency. Box *et al.* [11] and others have studied its optimality in terms of minimizing mean squared prediction errors for IMA(1) models; Cox [21] shows that it is effective for AR(1) models when parameter φ is larger than 1/ 3. In SPC the EWMA statistic is also an effective control chart for detecting small and medium mean shifts for both independently and identically distributed (i.i.d.) and autocorrelated processes (Lucas and Saccucci [34]; Montgomery and Mastrangelo [38]; Zhang [66]).

The relationship between EPC and SPC through prediction has been recently explored in many industrial applications. To make an appropriate selection between the two approaches in practice, it is important to identify disturbance structures and strengths of the two control methods to influence the process. Here we present four categories of on-going research and application of the two quality control approaches.

- If a process is not correlated, there is no need to employ EPC schemes and traditional SPC control charts should be used for identifying assignable cause variations;
- When data are correlated, the possibility of employing EPC techniques should be examined and SPC control charts are called for to monitor autocorrelated processes if no feasible EPC controller exists;

- If appropriate controllers are available, EPC control schemes can be employed to compensate for the autocorrelated disturbance. However, no single EPC controller system can compensate for all kinds of potential variations; and
- To identify and understand the cause of process changes, a unified control framework should be applied to regulate a process using feedback control while using the diagnostic capability of SPC to detect unexpected disturbances to the process.

The integration of EPC/ SPC looks for ultimate opportunities of quality improvement by integrating and combining the strengths of EPC and SPC among various levels of control that may be incorporated into a manufacturing system. Run-to-run (R2R) or sequential optimization and control is a typical realization of EPC/ SPC integration in semiconductor manufacturing (Moyne *et al.* [40]; Rashap *et al.* [45]; Ruegsegger *et al.* [48]). The R2R controller is a model-based process control system in which the controller provides recipes (inputs) based on post-process measurements at the beginning of each run, updates the process model according to the measurements at the end of the run, and provides new recipes for the next run of the process. It generally does not modify recipes during a run because obtaining real-time information is usually very expensive in a semiconductor process and frequent changes of inputs to the process may increase the variability of the process's outputs and even make the process unstable. A block diagram of such a R2R controller is shown in Figure 2.

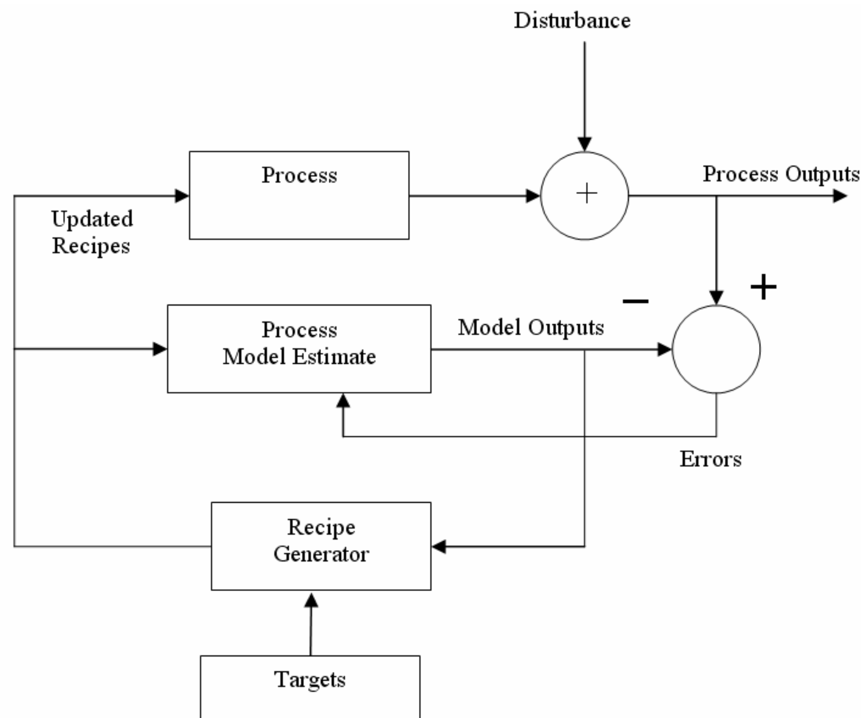

Figure 2. Structure of run-to-run controller.

A good R2R controller should be able to compensate for various disturbances, such as process drifts, process shifts due to maintenance or other factors, model or sensor errors, etc. Moreover, it should be able to deal with limitations, bounds, cost requirement, multiple targets and time delays that are often encountered in real processes. The initial R2R process control model can be derived from former experiments using statistical methods such as the

response surface model (RSM). When the controller is employed online, the model within the controller is updated according to the new measurements from run to run. A typical R2R system consists of three components: diagnosis module, gradual module, and rapid module (Sachs *et al.* [49]).

- Diagnosis module. It is a generalized SPC to distinguish between slow drifts and rapid shifts and decide if the process is running in accordance with the current process model. Since the inputs experience small changes, it is generally impossible to apply standard control charts to monitor the outputs. Mandel [37] suggests monitoring the prediction errors; Zhang [65] proposes cause-selecting control charts to determine which of the input or output is responsible for the out-of-control situation. In consequence, this module determines which of the following gradual or rapid modes is engaged.

- Gradual module. This module uses historical data to linearly update process models by giving less weight to old data. A pure I control is typically employed when the process can be well approximated by linear models. Assume D_t is an IMA(1) process, $D_t = D_{t-1} + \varepsilon_t - \theta\varepsilon_{t-1}$ where ε_t is a white noise, equation (1) can be generally rewritten as,

$$e_t = \alpha_t + gX_{t-1} + \varepsilon_t \tag{8}$$

where $\alpha_t = \alpha_{t-1} + (1-\theta)\varepsilon_{t-1}$ is the mean level of the disturbance. The optimal predictor α_t is the EWMA statistic $a_t = \omega(e_t - gX_{t-1}) + (1-\omega)a_{t-1}$ where $0 \le \omega \le 1$ is the fixed discount factor and $\omega = 1-\theta$ if θ is known (Box, Jenkins, and Reinsel, 1994). The recipe is set at $X_t = (\tau - a_t)/\ g$.

- Rapid module. This module quickly updates the process model based on changes detected by the diagnosis module. It must accomplish tasks such as estimating the magnitude and location of the disturbance, assessing sequentially the probability that a change actually took place given new available data, and using estimations of the disturbance to prescribe control actions (Sachs *et al.* [49]).

Significant research on the design of adaptive and robust controllers for the gradual control module exists. Double exponential forecasting method (Bulter and Stefani [15]; Castillo [17]) has been proposed using a Predictor Corrector Controller (PCC) to eliminate the impact of machine and process drift. Other control methods include Optimized Adaptive Quality Control (Castillo and Yeh [18]), Kalman filter (Palmer *et al.* [42]), set-value methods (Baras and Patel [10]), and machine learning methods such as Artificial Neural Network (Smith and Boning [52]). To facilitate the rapid module, Chen and Elsayed [19] provide a Bayesian estimation method for detecting the shift size and estimating the time of the shift; Yashchin [63] proposes an adaptive EWMA estimator of the process mean; Pan and Castillo [43] investigate using CUSUM charts in conjunction with sequential adjustments to improve the average squared deviations. However, the residuals from the gradual module are generally autocorrelated due to modeling errors and process drifts. The following section provides a review of SPC methods for monitoring autocorrelated processes and EPC systems.

4. SPC Methods for EPC/ SPC Systems

To develop efficient tools for monitoring EPC/ SPC systems, it is important to understand the impact of autocorrelation on the performance of control charts. Many authors have found that the presence of autocorrelation has a substantial and detrimental

effect on the statistical properties of control charts developed under the i.i.d. assumption. First, the standard deviation of the underlying process is often under-estimated when it is estimated from moving range and the first-lag autocorrelation is positive because

$$E(\hat{\sigma}_{MR}) = E(\overline{MR}/d_2) = \sigma\sqrt{1-\rho_1} \tag{9}$$

where ρ_1 is the first-lag correlation coefficient of the underlying process (Cryer and Ryan [22]). Second, because of the systematic nonrandom patterns of the autocorrelated data, it becomes difficult either to recognize a state of statistical control or to identify departures from the in-control state. Alwan and Robert [2] point out that the individual X chart based on the assumption of *i.i.d.* observations can be misleading if they are actually autocorrelated. Maragah and Woodall [36] quantify the effect of autocorrelation on the retrospective X-chart with and without supplementary rules. Therefore, to accommodate autocorrelations among observations, development of new control charts has received considerable attentions in the last decade.

One common SPC strategy for monitoring autocorrelated processes is to modify the control limits of traditional charts and then to apply the modified charts to the original autocorrelated data. Vasilopoulos and Stamboulis [59] provide an adjustment of control limits for Shewhart charts when monitoring autocorrelated processes. Johnson and Bagshaw [32] and Bagshaw and Johnson [9] provide the factor to adjust the critical boundary of CUSUM charts to correct the test procedure in the presence of correlation. The out-of-control performance of these adjustments has been investigated recently. Yashchin [62] shows that the CUSUM chart after adjustments can be seriously affected by mild autocorrelations. Zhang [66] studies the EWMA chart for stationary processes. Jiang *et al.* [30] extend the EWMA chart to a general class of control charts based on the autoregressive moving average transformation, the ARMA charts. The monitoring statistic of an ARMA chart is defined to be the result of a *generalized* ARMA(1,1) process applied to the underlying process $\{X_t\}$, i.e.,

$$Z_t = \theta_0 X_t - \theta X_{t-1} + \phi Z_{t-1} = \sum_{i=0}^{t-1} w_i X_{t-i} \tag{10}$$

where $w_0 = \theta_0$, $w_i = \theta_0(\phi-\beta)\phi^{i-1}\,\theta_0\ (i \geq 1)$ and $\beta = \theta/\theta_0$. θ_0 is chosen so that the sum of all coefficients w_i is unity when $t \to \infty$, i.e., $\theta_0 = 1+\theta-\phi$. The authors show that these charts could have good performance when certain chart parameters are chosen appropriately. Jiang and Tsui [28] extend it to higher-order ARMA charts which comprise a general class of control charts including SCC, EWMA, and PID charts as special cases.

4.1. Forecast-Based Monitoring Methods

A natural idea of monitoring an autocorrelated sequence is to transform the sequence into an *i.i.d.* or near *i.i.d.* sequence so that the "innovations" can be monitored by the traditional control charts developed for *i.i.d.* observations. This family of control chart is called the forecast-based *residual chart*. Alwan and Roberts [2] first propose to use Special Cause Chart (SCC) to monitor MMSE prediction errors. For simplicity, assume the underlying process $\{X_t\}$ follows an ARMA(1,1) process, i.e.,

$$X_t - uX_{t-1} = \varepsilon_t - v\varepsilon_{t-1} \tag{11}$$

where u and v are scalar constants and ε_t is white noise. The residuals can be obtained as $e_t = X_t - \hat{X}_t$ where $\hat{X}_t$ is the prediction of X_t given all information up to t–1. The MMSE

predictor can be written as $\hat{X}_t = vX_{t-1} + (u-v)X_{t-1}$. If the model is accurate, the prediction errors are approximately uncorrelated and then any conventional control charts can be utilized for monitoring the near i.i.d. prediction errors.

The SCC method has attracted considerable attention and has been further studied by many authors. Wardell *et al.* [60], [61] derive the run length distribution of the Shewhart chart applied to the residuals of an ARMA process; Vander Wiel [57] studies the performance of SCC's for integrated moving average IMA(0,1,1) models. In general, monitoring the i.i.d. residuals gives SCC charts the advantage that the control limits can be easily determined by means of traditional control charts such as the Shewhart chart, the EWMA chart, and the CUSUM chart. Another advantage of the SCC chart is that its performance can be analytically approximated.

The EWMA predictor is another alternative proposed by Montgomery and Mastrangelo [38] (M-M chart). Jiang *et al.* [29] further generalize the use of proportional-integrated-derivative (PID) predictors with subsequent monitoring of the prediction errors, i.e,

$$\hat{X}_{t+1} = X_t + \lambda_1 e_t + \lambda_2 e_{t-1} + \lambda_3 e_{t-2} \quad (12)$$

where $e_t = X_t - \hat{X}_t$, $\lambda_1 = k_P + k_I + k_D$, $\lambda_2 = -(k_P + 2k_D)$, and $\lambda_3 = k_D$. The PID-based charts monitor e_t and include the SCC, EWMA, and M-M charts as special cases. Jiang *et al.* [31] show that the predictors of the EWMA chart and M-M chart may sometimes be inefficient and the SCC may be too sensitive to model deviation. On the other hand, the performance of the PID-based chart can be predicted via chart parameters through measures of two "capability indices". As a result, for any given underlying process, one can tune the parameters of the PID-based chart to optimize its performance.

4.2. Generalized Likelihood Ratio Test (GLRT) Methods

Forecast-based residual methods involve only a single testing statistic and often suffers from the problem of a narrow "window of opportunity" when the underlying process is positively correlated (Vander Wiel [57]). For example, for monitoring an AR(1) process with ρ_1=0.9, a shift with size δ =1 will reduce to 0.1 from the second run after the shift occurrence due to forecast recovery. If an SCC missed the detection in the first place, it will become very difficult to signal since the mean deviation shrinks to only 10% of the original size. If the shift occurrence time was known, the "window of opportunity" problem is expected to be alleviated by including more historical observations/ residuals in the statistical hypothesis test. For the above AR(1) example, if a mean shift is suspected to take place at t–1, then residuals at both time t and t–1 can be used to obtain a likelihood ratio (LR) test for the hypothesis instead of e_t only, i.e., the test statistic is $(0.1e_t + e_{t-1})/\sqrt{1.01}$. If the hypothesis is true, this LR test has a signal-to-noise (SN) ratio of $1.1/\sqrt{1.01} \approx 1.09$ and consequently is more powerful than e_t whose SN ratio is 1.

A GLRT procedure can be obtained to test multiple shift locations (Vander Wiel [57]; Apley and Shi [5]). Assume the residual signature is $\{\delta_i\}$ $(t \geq 0)$ when a shift occurs, a GLRT based on residuals with window p is

$$\lambda_R = \max_{0 \leq k \leq p-1} \left| \sum_{i=0}^{k} \delta_i e_{t-k+i} \Big/ \sqrt{\sum_{i=0}^{k} \delta_i^2} \right| \quad (13)$$

This GLRT statistic, called *residual* GLRT, has been shown to be very effective to detect mean shifts if p is sufficiently large. However, Apley and Shi [5] indicate that it

strongly depends on the accuracy of signature. If a shift is not detected in the window, the signature applied in λ_R might no longer be valid and the test statistic is not efficient any more. Consequently, this GLRT procedure is insensitive to detect small shifts since they are very likely to be missed in the window.

Jiang [25] derives a generalized likelihood ratio test based on the original observations for different change point locations. Consider a p-variate random vector transformed from the univariate autocorrelated observations, $Y_t = (X_{t-p+1}, X_{t-p+2}, \ldots, X_t)'$, a step shift occurred at time t-k+1 has a signature,

$$d_k = (0,\ \ldots,\ 0,\ \overbrace{1,\ \ldots,\ 1}^{k})' \quad (1 \le k \le p)$$

and $d_k = (1, 1, \ldots, 1)'$ (k>p). The GLRT procedure (called *observational* GLRT) for testing these signatures is

$$\lambda_O = \max_{1 \le k \le p} \left| d_k' \Sigma^{-1} Y_t \Big/ \sqrt{d_k' \Sigma^{-1} d_k} \right| \tag{14}$$

where Σ is the covariance matrix of Y_t. It is important to note that, unlike the residual GLRT chart, one of d_k's always matches the true signature of Y_t regardless of the change point time. This grants a higher efficiency of the observational GLRT chart than the residual GLRT chart no matter how wide the window is. More importantly, the observational GLRT chart is essentially model-free while the residual GLRT chart is model-based. When other shift patterns present, a multivariate T^2 chart can be developed based on $T_t^2 = Y_t' \Sigma^{-1} Y_t$, which is essentially a GLRT test assuming no shift information (Apley and Tsung [6], Anderson [3]).

4.3. Monitoring EPC/ SPC Systems

Control charts developed for monitoring autocorrelated observations shed lights to monitoring integrated EPC/ SPC control systems. For example, the essential idea behind the forecast-based residual charts is mathematically similar to the pure EPC control strategy when the same forecasting scheme is used. In particular, monitoring the output of a MMSE controlled process has the same performance as the corresponding SCC charts. Similarly, the residual chart is equivalent to the associated monitoring component of the EPC/ SPC system.

Similar to the forecast-based methods, assignable causes have an effect that is always contaminated by the EPC control action and result in a small "window of opportunity" for detection (Vander Wiel [57]). As an alternative, some authors suggest that monitoring the EPC control action may improve the chance of detection (Box and Kramer [12]; Capilla *et al.* [16]). Kourti *et al.* [33] propose a method of monitoring process outputs conditional on the inputs or other changing process parameters. Jiang and Tsui [29] and Tsung and Tsui [55] demonstrate that monitoring the control action may be more efficient than monitoring the output of the EPC/ SPC system for some autocorrelated processes and vice versa for others. To integrate the information provided by process inputs and outputs, Tsung *et al.* [54] develop multivariate techniques based on Hotelling's T^2 chart and Bonferroni approach. Denote the multivariate vector by $Z_t = (e_t, X_{t-1})'$ which has covariance matrix Σ_Z, the T^2 chart monitors statistic

$$T_t^2 = Z_t' \Sigma_Z^{-1} Z_t \tag{15}$$

When mean shift patterns are known, similar to the GLRT procedures for monitoring autocorrelated processes, more efficient monitoring statistics can be developed following

the available signatures (Jiang [26]). For illustration purposes, the following section presents a Chemical-Mechanical Planarization (CMP) process to demonstrate the effectiveness of SPC methods in R2R control systems.

5. A Chemical-Mechanical Planarization Example

Chemical-Mechanical Planarization (CMP) of dielectric films is basically a surface planarization method in which a wafer is affixed to a carrier and pressed face-down on a rotating platen holding a polishing pad as shown in Figure 3 (Zantye *et al.* [64]). This enabling technology is used for the manufacturing of integrated circuits with interconnect geometries of less than 0.18 micron. Silica-based alkaline slurry is applied during polishing thus providing a chemical and mechanical component to the polishing process. The primary function of CMP is to smooth a nominally macroscopically flat wafer at the feature (or micro-level), i.e., planarize features. The post-polish nonuniformity (*NU*), measured by the ratio of the standard deviation of the post-polish wafer thickness to the average post-polish wafer thickness, is usually required to be less than 5% variation in film thickness across wafer. Therefore, to evenly planarize features across the whole wafer it is crucial to have a uniform material removal rate (*RR*) across the wafer. This removal rate uniformity, measured by the within wafer non uniformity, ensures that the entire wafer is uniformly reduced in height.

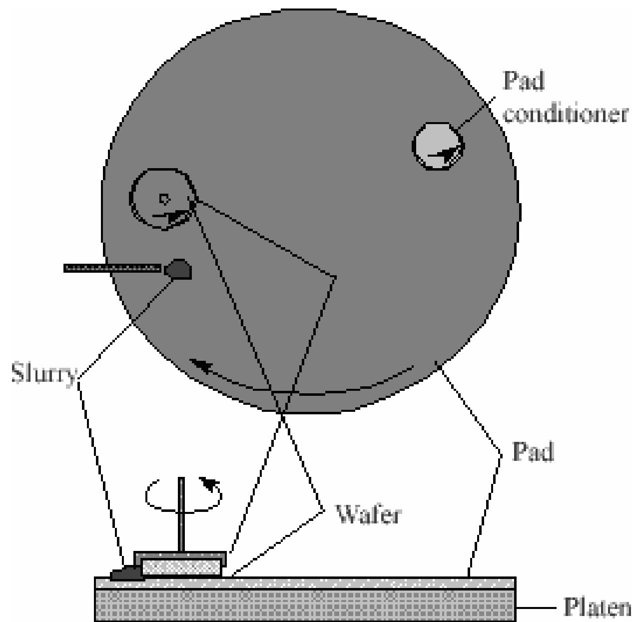

Figure 3. Schematic of a CMP system.

It is well known that CMP is governed by the Preston equation, which describes an empirical approximation of polishing rate in terms of applied pressure and relative velocity between polishing pad and wafer, i.e., $RR = K_p \cdot P \cdot S$ for removal rate, where K_p is Preston coefficient inversely proportional to elastic modulus of material being polished, P is down pressure, and S is pad-wafer relative speed (Preston [44]). The Preston's coefficient K_p depends on process variables such as slurry composition, pad properties, mechanical abrasion and chemical effects during polishing process. The Preston's equation is rather rough and many authors have developed modifications considering the mechanical and

chemical properties of wafer, polishing pad and slurry (see e.g., Cook [20], Tseng and Wang [53], Runnels *et al.* [46]). In order to control uniformity, one alternative is to reduce the non-uniformity of the pressure and velocity distribution. However, as pads wear, *RR* usually decreases and coincides with increasing *NU* over time, even with conditioning. This requires a substantial use of SPC monitoring to check the performance of the R2R controller. For illustration, we consider adjusting pressure ratio to compensate for pad wear.

Figure 4 presents an experiment of material removal rate under a R2R control system. Due to the nonuniformity of incoming dielectric, the output wafer nonuniformity may drift away from target if without EPC/SPC control. In addition, a wear problem starts from the 51st run on the polish pad. Now a EWMA (I) controller is employed to adjust the polish rate and the CMP nonuniformity of material removal rate is found closer to target, 1.5%, before the wear problem occurs but more than 2% afterwards.

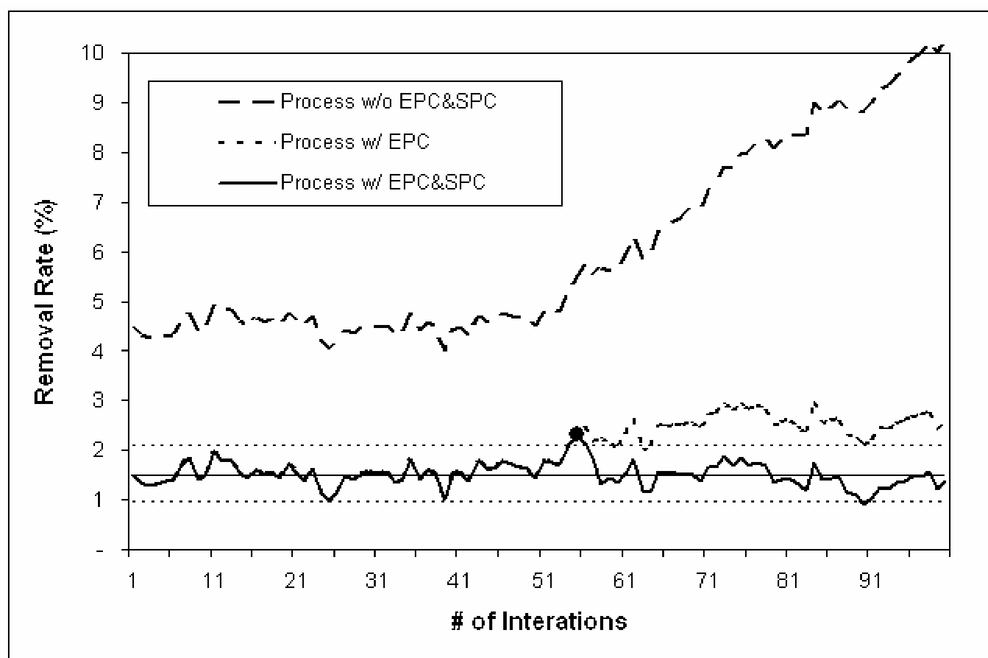

Figure 4. Output removal rate.

Note that, although the EWMA controller is designed to reduce incoming dielectric variations, the severity of the polish pad deterioration is also weakened (the drift has been reduced to a step shift). If a Shewhart chart is applied to monitor the EPC-CMP process, a signal will be triggered at the 54th run and the polish rate model can be updated to take into consideration the polish pad deterioration. The nonuniformity can be always maintained at 1.5% whatever the pad wear problem happens or not, showing the effectiveness of SPC methods in improving product quality.

6. Design of EPC/SPC Systems: Efficiency versus Robustness

Although EPC and SPC techniques share the same objective of reducing process variations and many similarities in implementation, the criterion for selecting SPC monitoring charts is fundamentally different from corresponding EPC controllers. For example, instead of minimizing the mean squared error/prediction error of a PID

controller, maximization of the chance of detecting shifts is always desired when designing a PID chart. Alternatively, signal-to-noise (SN) ratios developed in Jiang *et al.* [30] can be used and an ad hoc procedure is proposed for designing appropriate charts.

Taking PID chart as an example shown in Figure 5, two signal-to-noise ratios are crucial to the statistical performance of a PID chart. Denote σ_Z the standard deviation of charting statistic Z_t, μ_T (μ_S) the shift levels of Z_t at the first step (long enough) after the shift happens. The transient state ratio is defined by $C_T = \mu_T / \sigma_Z$ which measures capability of the control chart to detect a shift in its first few steps. The steady state ratio is defined by $C_S = \mu_S / \sigma_Z$ which measures capability of the control chart to detect a shift in its steady state. By selecting control chart parameters, these two ratios can be manipulated in the desired way so that the chance of detection is maximized.

In general, if the transient ratio can be tuned to a value high enough (say 4 to 5) by choosing appropriate PID parameters, the corresponding PID chart will be able to detect the shift quickly. On the other hand, if this ratio is smaller than 3, the shift will likely be missed at the transient state and needs to be detected in the later runs. In this case, the steady state ratio becomes more important for detecting the shift efficiently at the steady state. Although a high steady state ratio is helpful in detecting the shift in steady state, it may result in an extremely small transient ratio and make the transition of the shifts from the transient state to the steady state very slow. To make the chart detect the shift efficiently in the steady state, a balance is needed to make a tradeoff between the transient ratio and the steady state ratio when choosing the charting parameters. Generally, Jiang *et al.* [30] recommend the appropriate selection of chart parameters value to achieve C_S around 3 for balancing the values of C_T and C_S. This heuristic algorithm is also helpful in designing other types of SPC charts for autocorrelated or EPC process, e.g., the EWMA and ARMA charts.

One of the obstacles that prohibit the usage of SPC methods in monitoring autocorrelated or EPC processes is the robustness of a control chart. It is defined by how its run length distribution changes when the process model is mis-specified. Since residuals are no longer *i.i.d.*, reliable estimates of process variations should be used (Boyles [14]; Alexopoulos *et al.* [1]). Moreover, even though a robust estimator of standard deviations can be obtained, a more sensitive control chart such as PID charts could still be less robust comparing to less sensitive control charts such as MMSE-based SCC charts. For example, Tsung *et al.* [56] and Luceno [35] conclude that PID controllers are generally more robust than MMSE controllers against model specification errors. However, Jiang *et al.* [29] show that, PID charts tends to have a shorter "in-control" ARL when the process model is mis-specified since model errors can be viewed as a kind of "shift/ deviation" from the "true" process model.

The non-robustness of sensitive control charts seems discourage development of more efficient control charts and a trade-off is necessary between sensitivity and robustness when selecting control charts for monitoring autocorrelated processes. Apley and Lee [4] recommend use a conservative control limit for EWMA charts for monitoring MMSE residuals. By using worst-case estimation of residual variance, the EWMA chart can be designed to be robust in the in-control state with a slight loss of efficiency in the out-of-control state. This design strategy is very helpful and can be generalized to other SPC methods for monitoring autocorrelated or EPC processes.

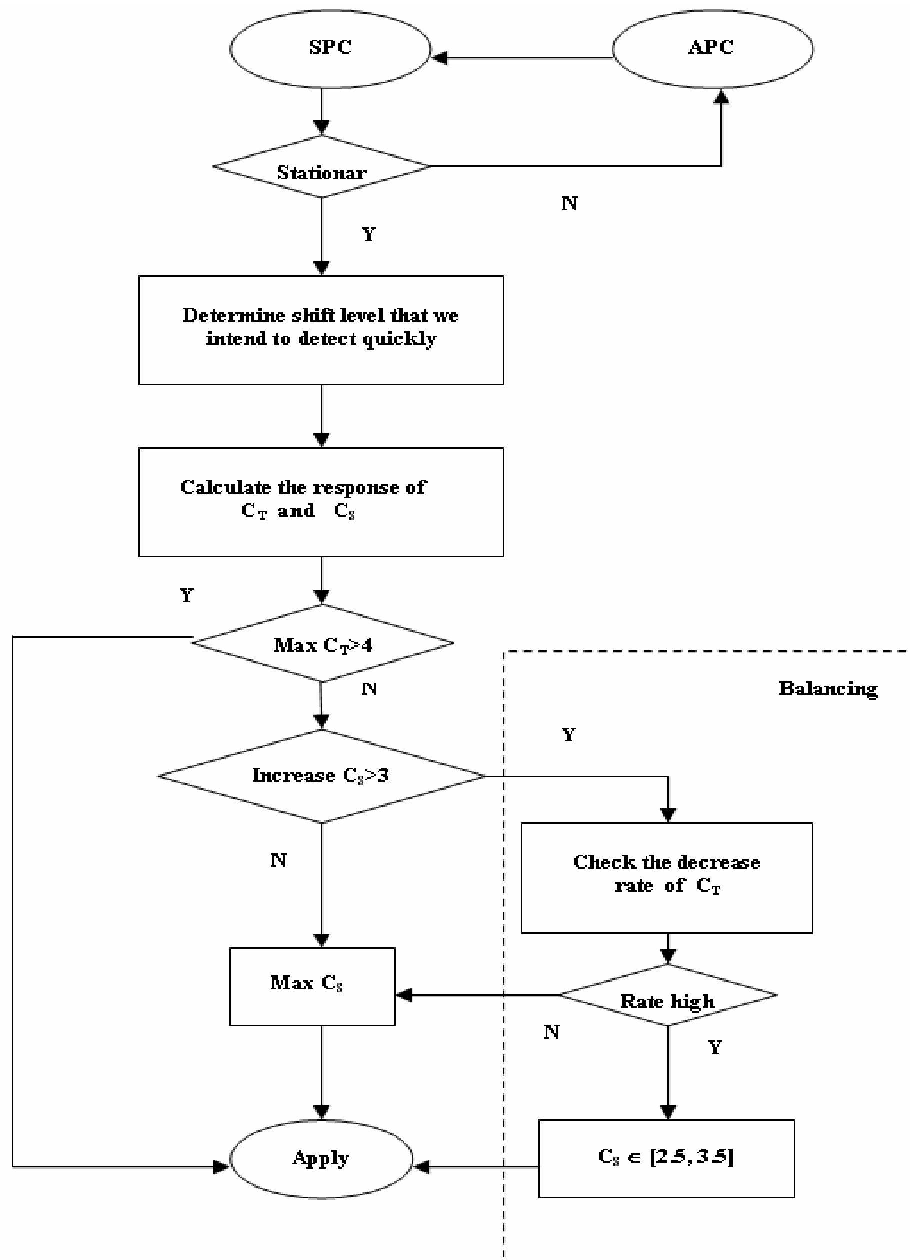

Figure 5. Design of PID charts.

7. Concluding Remarks

This paper provides a review of current EPC and SPC techniques and their applications in parts and process industries for quality improvement. The two classes of methods can be linked and integrated in a unified quality control framework. While much attention has been focused on developing various efficient and robust EPC controllers in literature, we emphasize the crucial task of monitoring autocorrelated processes and EPC systems. The case study demonstrates the effectiveness of the EPC/ SPC integration.

Acknowledgement

We are grateful to the associate editor for many insightful suggestions. This research is partially supported by NSF DMI-0200224.

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