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Research

Transition Monitoring and Adjustment for Dynamic Systems in a Process Improvement Environment

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In manufacturing applications, we often encounter process transitions due to a changeover in the production or perhaps an unknown perturbation. The main process improvement goal is to shorten the transition time by monitoring the process in order to quickly identify the start and end of the transition period and by actively adjusting the process during the transition. To address these issues, we propose a transition monitoring and adjustment methodology. A polymer process is used to illustrate this methodology. Using simulation, we characterize the impact of the transition adjustment on the effectiveness of monitoring. We show that the adaptive monitoring procedure is robust to small transition adjustments, thus supporting a complimentary application of process monitoring and process adjustment to improve process transitions. Copyright © 2005 John Wiley & Sons, Ltd.

KEY WORDS: statistical process control (SPC); process adjustment; exponentially weighted moving average (EWMA); transitions; process improvement

1. INTRODUCTION

Traditional control charts, when used as process monitoring tools, are based on the assumption that the process data are independent with a constant mean. However, modern manufacturing systems often generate data that violate these assumptions. Control charting is therefore frequently challenged by issues such as autocorrelation, process transitions, and process adjustments to improve operational efficiency.

With the advance of measurement technologies, process data are routinely recorded using on-line sensors and machine vision systems. A common consequence of using these measurement technologies is that the resulting process data are autocorrelated, especially when collected at close intervals. Harris and Ross[1] have shown that the false alarm rate for traditional control charts increases in the presence of autocorrelation. A common approach to addressing autocorrelation in control charting is to filter out the autocorrelated structure and apply traditional control charts to the forecast residuals (see, e.g., Berthouex *et al.*[2], Alwan and Roberts[3], and Montgomery and Mastrangelo[4]).

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While control charts are used to monitor processes over time to detect assignable causes so that corrective efforts can be undertaken to remove the root causes, process adjustment techniques actively adjust the controllable variable to maintain a process on target; see, for example, Box and Luceño[5], Box *et al.*[6], Ogunnaike and Ray[7]).

Manufacturing industries have also witnessed significant increases in the rate of production changeovers driven by global competition and evolving customer needs and expectations. A changeover usually involves a change in input variables so that a different product may be obtained. Examples of changeover operations may include grade changes, style changes, recipe changes and raw material changes. However, the output process may not respond to these changes instantaneously. That is, an inherent transition period may be induced prior reaching a new steady-state process mean. Such a response is especially evident when the system exhibits dynamic behavior.

When numerous process transitions occur on a daily basis, there is an opportunity to manage these transitions to improve the operational performance of the overall manufacturing system. The use of statistical control techniques to address the process transition problem has been investigated: Nembhard and Mastrangelo[8] studied the utility of integrating monitoring and adjustment methods to address the process transition problem for a dynamic system with stationary disturbances, and Nembhard *et al.*[9] investigated the sensitivity integrated monitoring and adjustment using non-stationary disturbances. These two investigations demonstrated the utility of the moving centerline exponentially weighted moving average (MCEWMA) control chart procedure based on exponentially weighted moving average (EWMA) forecasts to monitor a process having a significant transition period. This control chart procedure effectively acknowledged the inherent trend during the transition period as opposed to the more traditional methods. However, an increase in false alarms during the transition period is likely due to inadequate EWMA forecasts, suggesting an opportunity to improve the transition monitoring function. Advancing on this opportunity, Nembhard and Kao[10] suggested an adaptive forecast-based monitoring procedure, the adaptive exponentially weighted moving average (AEWMA), which is based on varying the forecast parameter during transition period.

This paper proposes a transition monitoring and adjustment methodology, where the objective is to improve the process by actually *shortening* the transition period. That is, the transition period is viewed as an impediment to the normal performance of the manufacturing system, due to its counter-productive and time-delaying nature. This is certainly the case in the polymer processing context that we use here to illustrate the methodology. The critical components of the methodology are as follows. The process is monitored to identify both the start of a transition (SOT) and the end of a transition (EOT), as well as special causes. Until the transition begins, the process is monitored with an EWMA statistic enhanced using a tracking signal. When the SOT is identified, a transition adjustment is made (again, for the purpose of shortening the transition period) while the process is simultaneously monitored using an AEWMA statistic until the EOT is identified. This proactive effort to improve the process, however, tends to alter the transition *profile* of the transition period. As such, in order to establish the value of the methodology, it is critical to evaluate the sensitivity of the AEWMA procedure to provide appropriate guidance regarding the transition adjustment. Our evaluation criterion is based on the false alarm and detection rates of the monitoring procedure.

This paper is organized as follows. In Section 2, we motivate the process transition problem by examining a plastic extrusion process, and how transition adjustment can be implemented to shorten the transition period. Section 3 introduces the mechanics of the transition monitoring and adjustment methodology. In Section 4, the sensitivity of the AEWMA procedure is studied when transition adjustment is administered. Section 5 gives a summary of the paper.

2. PROCESS TRANSITION IN POLYMER PROCESSING

2.1. Process transition motivation

Over the years, the plastics industry has witnessed an increasing demand for more diversified products as well as customized products in small quantities. It has become a norm for plastics manufacturers to deal with a myriad of product switching operations (such as color, material, and grade changes) on a daily basis. Color, for instance, has become an important aesthetic element of surface quality since it provides an instant appeal to customers. In order to make different color plastic products, a production line must switch from one resin color to another. Such an operational change, however, generates a color transition in the plastic products. In other words, a substantial period of mixed-color plastic is expected before the new target color is fully achieved.

The economic impact stems from both material scrap and also unproductive labor and machine time. Since the SOT and EOT for the color transition are usually not known, much product is often wasted during a buffer time that is used as a margin safety. Using mechanistic modeling such as residence time studies (Pinto and Tadmor[11]) for color switching operations is impractical due to the limited time available and the complexity of process operations. This suggests that transition monitoring and adjustment procedures could make a significant contribution to addressing the process transition problem.

2.2. *Experimental Procedure*

A single-screw extruder is used to execute the color switching operation, which induces a color transition. The surface color information is captured and processed on-line by a machine vision system. A description of the experimental apparatus and method are given below.

A laboratory scale single-screw extruder was used to perform the color switching experiments. The extruder has a diameter of 20 mm and a length to diameter (L/D) ratio of 25:1. A slit die is attached to the end of the extruder to form a strip of plastic tape. A mechanical forming roller is placed at the end of the extruder to continuously pull and guide the extruded tape from the die. The processing variables are the barrel temperature profile with zones 1–4 and screw speed. High-density polyethylene (HDPE) resin is used as the input material.

An on-line machine vision system was also set-up next to the extruder to capture and process the surface information of the extruded tape at fixed time intervals. The components that make up this machine vision system are a charge coupled device (CCD) camera, a frame grabber, a desktop PC, and an imaging software program. The camera is positioned and focused on the extruded tape to capture images of its surface. The frame grabber is a device that facilitates the interface between the camera and the computer. Essentially, it translates the still image frames taken from the camera into digital information readable by the computer. The imaging software then processes and writes the frames of image data, in hue–saturation–brightness (HSB) format, to a text file. Figure 1 shows a screen snapshot of the imaging software capturing image data.

To emulate the color switching process in plastics manufacturing, we introduced a batch of yellow color resin mix into the extruder, followed by a batch of red color. Image data for the entire color transition process were then recorded by the machine vision system. The common practice for making colored plastics is to prepare the resin mix by adding the desired colorant. For instance, to prepare a batch of yellow color resin mix, yellow color pellets are blended with a portion of HDPE resin according to the let-down ratio that defines the coloring power of the colorant.

2.3. *Improving the color transition process*

As a start, we performed a yellow-to-red color switching operation on the extruder system to gain an appreciation of the significance of the color transition. The temperature profiles were set at 170, 180, 190, and 200 °C respectively and the screw speed was set at 40 rpm. The surface color characteristics of the extruded tape were recorded immediately by the machine vision system as it exited the die. Figure 2 shows a run chart of the average color intensity of the tape surface taken at fixed time intervals.

Note that we have deliberately changed the surface color characteristics of the extruded tape from one process mean color (0.84 units) to another (0.4 units). However, as a consequence of the dynamic nature of the extrusion system, which is a non-instantaneous response, there is a significant intermediate transition period. Note further that the process takes approximately 40 time units to reach the new color level. An important question arises: Can we improve upon the color transition by shortening the transition period?

We identified screw speed as a controllable variable that would directly affect the color transition at the output. A simple transition adjustment method was devised to achieve the process improvement objective of reducing

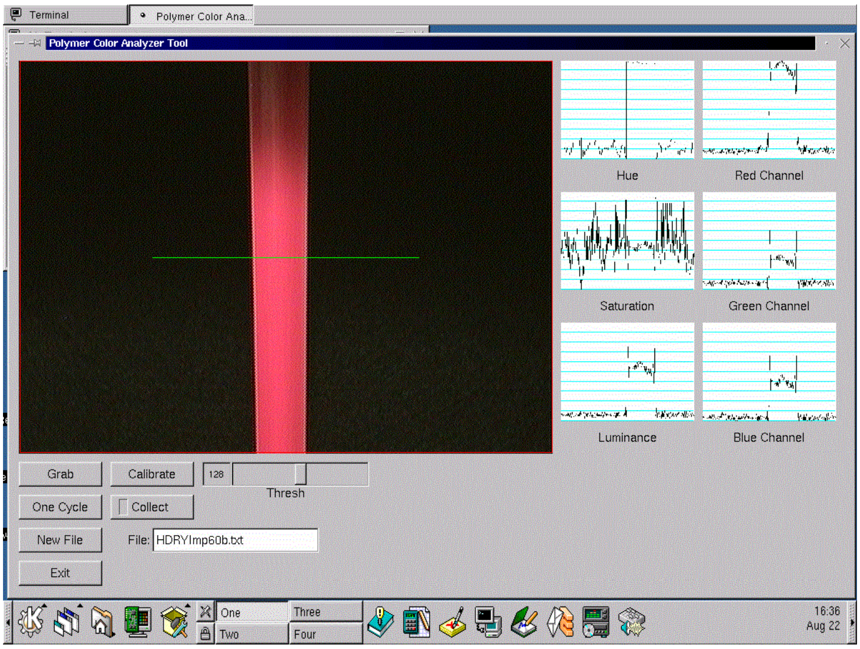

Figure 1. A snapshot of the software that captures the image data

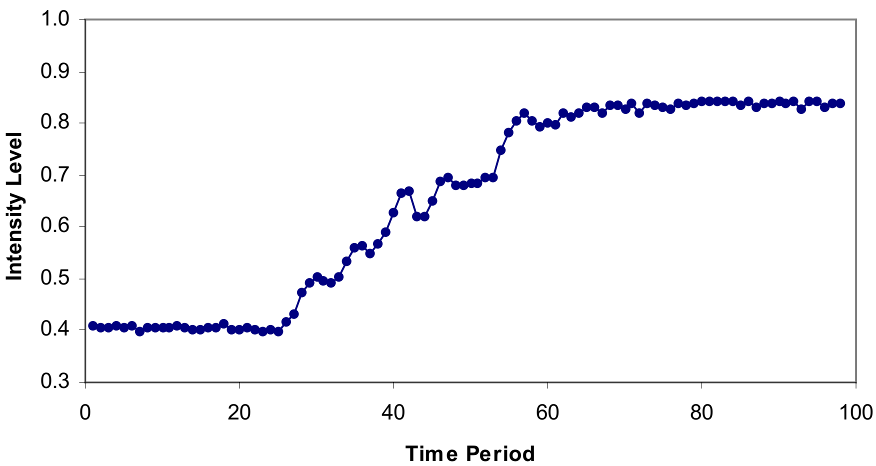

Figure 2. Time series plot of the color intensity in a color transition operation

the color transition period. It involves increasing the screw speed to 60 rpm as soon as the color transition begins, and then decreasing the screw speed to the original setting (40 rpm) when it ends.

We implemented this transition adjustment method on the color switching operation and plotted the average color intensity of the tape surface over time in Figure 3. Clearly, adjusting the screw speed for the transition period has reduced the color transition time. Increasing the screw speed further (for example, to 80 rpm) will further reduce the color transition time as shown in Figure 4. However, adjusting the color transition modified the transition profile from gradual to abrupt.

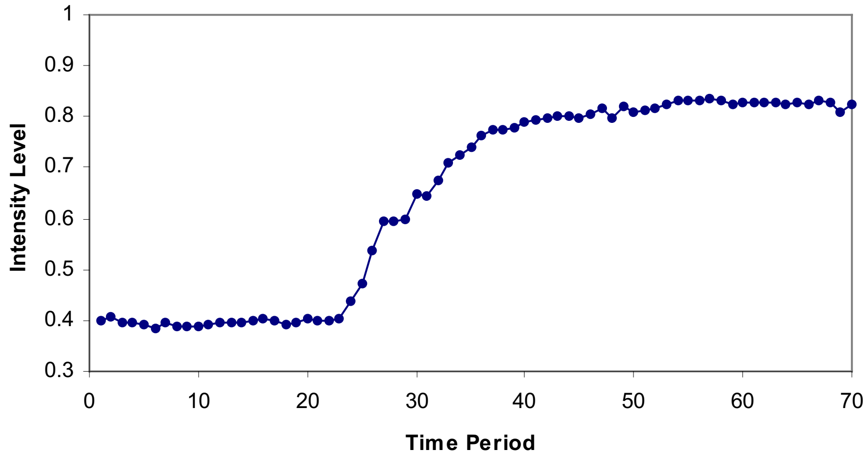

Figure 3. Color intensity over time when the screw speed is adjusted to 60 rpm for the transition period

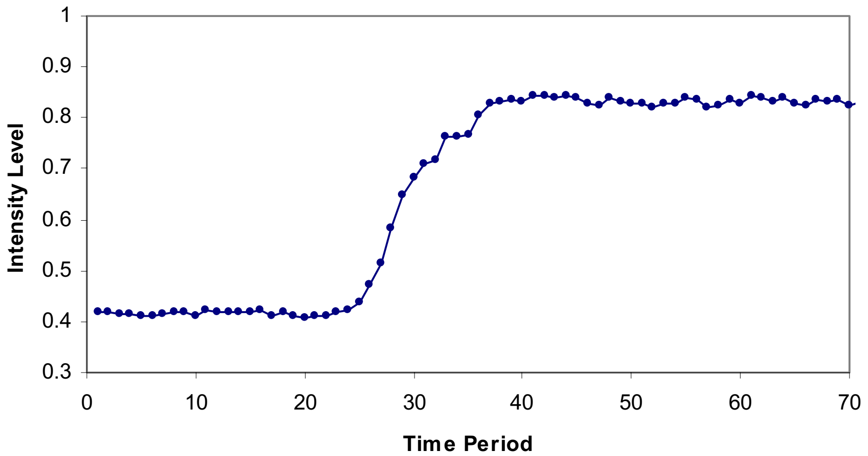

Figure 4. Color intensity over time when the screw speed is adjusted to 80 rpm for the transition period

3. THE TRANSITION MONITORING AND ADJUSTMENT METHODOLOGY

3.1. Forecast-based EWMA and tracking signal test

Several authors have suggested the forecast-based EWMA procedure to monitor autocorrelated observations (see, e.g., Alwan and Roberts[3] and Montgomery and Mastrangelo[4]). The approach uses the EWMA statistic to account for the autocorrelated structure, and then applies traditional control charts, such as the individuals, EWMA or CUSUM charts, to the forecast residuals.

The forecast-based EWMA statistic is given by

$$\hat{Y}_t(1) = \lambda Y_t + (1 - \lambda)\hat{Y}_{t-1}(1) \tag{1}$$

where $0 < \lambda \leq 1$ is the smoothing constant and $\hat{Y}_t(1)$ is the one-step-ahead forecast made at the end of period t for the future observation Y_{t+1}. In control charting, typical values of λ are between 0.05 and 0.25. For simplicity, we apply the individuals control chart to the sequence of forecast residuals, $e_t = Y_t - \hat{Y}_{t-1}(1)$. The centerline,

$\bar{e}$, of the individuals chart is defined as

$$\bar{e} = \frac{\sum_{i=1}^{t} e_i}{t}$$

The control limits for the individuals chart are

$$UCL_e = \bar{e} + L\frac{\overline{MR}}{d_2}$$
$$LCL_e = \bar{e} - L\frac{\overline{MR}}{d_2}$$

where $\overline{MR} = \sum_{i=2}^{t-1} MR_i/(t-1)$, $d_2 = 1.128$, L is the control limit constant, and the moving range for each observation, $MR_i = |x_i - x_{i-1}|$, for $i = 2, \ldots, t-1$, is used to estimate the variance of the forecast residuals.

The tracking signal is normally used to monitor the accuracy of a forecasting system (Brown[12]). A tracking signal measures the deviation of the estimated forecast error from zero relative to the variation of the statistic. Large deviations suggest that the performance of the forecasting system has deteriorated and that the underlying form of the time series has changed. Mastrangelo and Montgomery[13] suggested supplementing the forecast-based monitoring procedure with the smoothed-error tracking signal for efficient trend shift detection.

The smoothed-error tracking signal, S_t, is the absolute value of the fraction given by the weighted sum of all past one-step-ahead forecast errors, $Q_t(1)$, divided by the standard deviation of the one-step-ahead forecast errors, $\hat{\Delta}_t$:

$$S_t = \left|\frac{Q_t(1)}{\hat{\Delta}_t}\right| \tag{2}$$

The smoothed error statistic, $Q_t(1)$, is given by

$$Q_t(1) = \alpha e_t(1) + (1-\alpha)Q_{t-1}(1)$$

where α is the smoothing constant, $0 < \lambda \le 1$ and $0 < \alpha < 1$. This statistic applies the exponential smoothing concept by giving more weight to recent forecast errors than older ones. The standard deviation of the one-step-ahead forecast errors is estimated by the mean absolute deviation (MAD),

$$\hat{\Delta}_t = \alpha|e_t(1)| + (1-\alpha)\hat{\Delta}_{t-1}$$

where α is a smoothing constant typically chosen between 0.05 and 0.15. The MAD is essentially a weighted average of all past and current forecast errors where the weights decrease geometrically. The value of S_t is compared with a constant K_S, where $0.2 \le K_S \le 0.5$. If $S_t > K_S$, we say that the forecasting system is inaccurate. Adopting this statistical test, the smoothed error tracking signal can be used to signal for the SOT. To guard against unwarranted false alarms, two to three consecutive signal firings are commonly used.

Nembhard and Kao[14] use the forecast-based EWMA procedure to monitor autocorrelated data when process transitions are anticipated. By supplementing the monitoring procedure with the smoothed-error tracking signal, they devised a sign test to estimate the EOT. The sign test is based on the first finite difference of S_t in (2),

$$\nabla S_t = S_t - S_{t-1} \tag{3}$$

where ∇ is the backward difference operator. A signal is fired if ∇S_t in (3) switches sign. This statistical test is analogous to the first derivative test for finding the inflection points of a continuous differentiable function. It exploits the characteristic of S_t in that it eventually ‘forgets’ about the past large errors once the forecasting system returns to normal accuracy. Consecutive firing rules are again used to guard against false alarms due to process disturbances and measurement error.

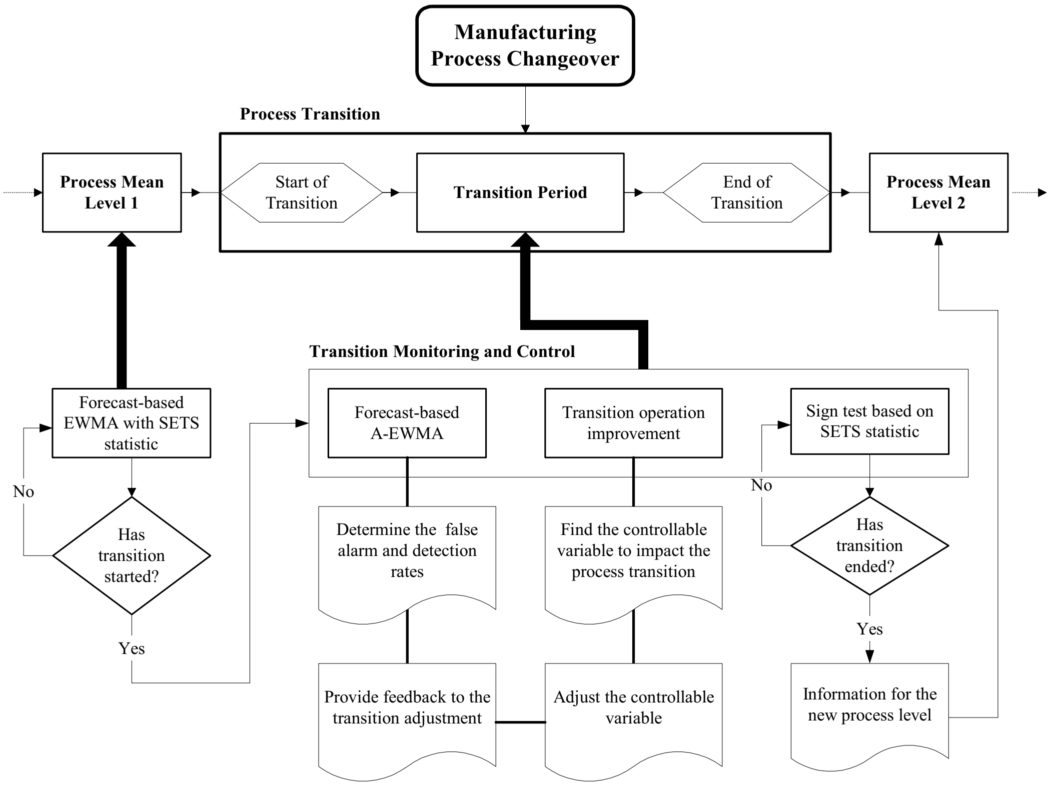

Figure 5. A process chart of the transition monitoring and adjustment methodology

3.2. *The AEWMA procedure for process transition*

The AEWMA procedure is used to effectively monitor the transition period, usually characterized by an inherent trend (Nembhard and Kao[10]). This monitoring procedure follows the concept of the forecast-based EWMA procedure except for its adaptive capability. The one-step-ahead forecasts of the AEWMA procedure is

$$\hat{Y}_t(1) = \begin{cases} \lambda Y_t + (1-\lambda)\hat{Y}_{t-1}(1), & t < T_{\mathrm{SOT}} \\ \lambda_t^* Y_t + (1-\lambda_t^*)\hat{Y}_{t-1}(1), & t \geq T_{\mathrm{SOT}} \end{cases} \tag{4}$$

where T_{SOT} is the time period in which the transition begins and the asterisk and t on the λ parameter indicates that the best value of the smoothing constant changes over time when $t \geq T_{\mathrm{SOT}}$.

Equation (4) implies that before a process transition, the usual forecast-based EWMA with λ constant is used to monitor the constant mean process, which complies with (1). However, when a process transition is encountered, the λ value is adapted as the process develops towards a new process level. The λ_t^* parameter in (4) is determined based on the minimum mean square error (MSE) of prediction criterion. The path of λ_t^*, for $t \geq T_{\mathrm{SOT}}$, decays exponentially over time. As such, λ_t^* will eventually converge back to the original λ value. The computation of λ_t^* is given in Nembhard and Kao[10].

3.3. *Methodology synthesis*

A block diagram explaining the application of the transition monitoring and adjustment methodology is shown in Figure 5. At the top, the Manufacturing Process Changeover block represents the agent for inducing a significant process transition between two distinct process levels. The process transition includes the transition period, SOT and EOT. Arrows signify the sequence of occurring events.

The lower portion of the chart illustrates the application of transition monitoring and process adjustment as a means to improve the transition operation. We begin with the forecast-based EWMA procedure applied to a certain process level. This control charting procedure is supplemented with the tracking signal statistic to identify the SOT. When a signal is fired to indicate a process transition has begun, this information is used to initiate the monitoring and adjustment procedures for the transition period. To monitor the transition period, the AEWMA procedure is used. Meanwhile, adjustments are applied to the controllable variables to shorten the transition period. Lastly, a sign test based on the tracking signal statistic is initiated to test for the EOT. A signal fired by the sign test indicates that the transition is over, i.e. a new process level has been established. This information can be used to facilitate the continual application of appropriate control charts for the new process level.

The primary goal of adjusting the process transition as a means of improving the transition operation is to shorten the transition period. In the extrusion case, the screw speed and the transition period exhibit a strong, direct relationship and are easily identified. We note that for more complex systems, the improvement effort is often iterative and evolutionary as more knowledge is gained about the system (Box[15]). This is often achieved using statistical methods. Design of experiment (DOE) methods (Box *et al.*[16]) are widely used to identify critical input variables that affect the output response. Response surface methodology (Box and Draper[17]) defines the critical variables based on a set of conditions that optimizes the output response. When experimenting on a full-scale production plant where only small increments of the experimental variables are allowed, evolutionary operation (EVOP) is useful (Box[18]). Further, time series modeling techniques are essential to feedback adjustment applications (see, e.g., Box *et al.*[6]). More recently, Nembhard and Valverde-Ventura[19] have suggested a synthesis of DOE and statistical control where certain types of process deviations are suspected *a priori*.

A key aspect of this methodology is that by adjusting the transition period, we have altered the transition profile. The impact on the AEWMA procedure due to a transition adjustment becomes important. Knowledge about the sensitivity of the AEWMA procedure can be used to help make the appropriate transition adjustment. Such an interaction between the AEWMA procedure and transition adjustment is illustrated in the flowchart. The following section evaluates the sensitivity of the AEWMA procedure to provide appropriate guidance regarding the transition adjustment based on false alarm and detection rates.

4. PERFORMANCE ANALYSIS OF THE AEWMA PROCEDURE

4.1. Mathematical model for process transition

Two widely used mathematical models for representing a dynamic, stochastic system are the autoregressive integrated moving average (ARIMA) time series models and difference equations. To provide a model representation of the color transition process as seen in Figures 2 and 3, Nembhard and Kao[10] used a linear combination of the first-order dynamic and first-order autoregressive (AR(1)) processes. The equation of a process transition beginning at time T_0 for the output, Y_t, having a first-order dynamic with an AR(1) process disturbance is given by

$$Y_t = Mg(1 - \delta^{t-T_0}) + \frac{1}{1 - \phi B} a_t \tag{5}$$

where $0 \leq \delta < 1$ is the degree of inertia for the process dynamics, M is the transition magnitude, g is the steady-state gain, $-1 < \phi < 1$ is the constant of the autoregressive process, $BY_t = Y_{t-1}$ is the backshift operator, and a_t is a white noise process with mean zero and variance σ_a^2.

Note that the value of δ has a strong influence on the shape profile of the transition period. When δ is close to one, the transition profile tends to be a gradual trend. As δ decreases, the transition profile will become more abrupt. Therefore, a mathematical approach for the transition adjustment, which tends to alter the transition profile from gradual to abrupt, is to decrease the value of δ for the underlying first-order process.

4.2. *Sensitivity analysis of the AEWMA procedure*

We evaluate the sensitivity of the AEWMA procedure when the δ value of the underlying first-order process has changed. To provide a platform for simulation analysis, we model the color transition process shown in Figure 2 to get $\hat{\delta} = 0.95$ for the first-order process as our baseline. The control charts for monitoring the transition period follow the AEWMA procedure given in Section 3.2. Using the estimated δ from the baseline color transition process, the path of λ_t^* can be determined when no transition adjustment has been administered.

The evaluation criterion is based on the in-control ARL (or false alarm) and detection rate. The ARL is a measure of the average number of samples obtained before an out-of-control signal occurs. There is a 'window of opportunity' for detecting the out-of-control condition between the beginning of the process upset and the time when the transition period ends. So the detection rate will estimate the proportion of runs in which signals occur between the start of a process shift (or upset) and the time where the transition period ends, i.e. the 'window of opportunity'.

To study the sensitivity of AEWMA procedure, we increase the δ value of the underlying first-order process (denoted as δ_1) while maintaining the path of λ_t^*, which was originally determined using $\delta_0 = 0.95$. The lower bound for δ_1 study range is 0.75, as its transition profile is rather abrupt. We also explore a range of values for the transition magnitude, M, and the control limit constant, L. For each scenario, 10 000 simulations were performed to compute the false alarm ARLs and detection rates. Note that the first 100 forecast residuals are not used to allow for system warm-up.

Figure 6 displays the in-control ARLs for the AEWMA procedure for various transition magnitudes, control limit constants, and changes in the degree of inertia. Consistent with our expectations, the in-control ARL improves with increasing L. Note, however, that the improvement in ARL is not constant as the interval between two L levels increases as L increases. For a small transition magnitude, $M = 5$, the in-control ARL of the AEWMA procedure is remarkably insensitive to a change in the underlying first-order process as illustrated by the parallel lines for the range, $0.75 \leq \delta_1 \leq 0.925$. The implication is that the desired false alarm rate may be preserved even if process transitions are adjusted to shorten the transition period. When the transition magnitude becomes large, as in the $M = 15$ case, the in-control ARL deteriorates rapidly as the underlying first-order process changes from gradual to abrupt, i.e. δ_1 decreases. In other words, the ARL is sensitive to process transition adjustment for larger transition magnitudes. Nevertheless, the sensitivity increases with decreasing L. This is especially true for the moderate transition magnitude, $M = 10$.

Since the in-control ARL results are more favorable for small transition magnitudes, we focus the evaluation of detection rates taken within the 'window of opportunity' for the $M = 5$ case. The detection rates of the AEWMA procedure for a small transition magnitude having small, medium, and large process shifts are plotted in Figure 7. There are clearly three distinct detection rate ranges. The detection rates for a 1σ process shift are clustered between 0 and 0.25, those for a 3σ process shift are between 0.41 and 0.72, and those for a 5σ process shift are between 0.95 and 1.0. The fact that detection rates increase as shift size increases is intuitive. For a small process shift, the detection rate is seen to decrease rapidly as δ_1 decreases. This situation may be improved by increasing L, but at the expense of reducing the detection rate. Further, as the shift size increases, the detection rate begins to stabilize with increasing δ_1. Therefore, the detection rate is more insensitive to process transition adjustment when larger process shifts occur.

As the detection rate improves with decreasing L, this generates a distinct trade-off with the in-control ARL criterion. From the in-control ARL result, we recommend implementing the transition adjustment when transition magnitudes are relatively small and using a control limit constant, $L > 3.1$, to maintain a relatively small false alarm rate. When the processes are characterized by moderate to large process shifts, we work with a fairly broad range of $0.75 < \delta_1 < 0.925$ and still maintain a decent detection rate.

5. *CONCLUSIONS*

In this global marketplace, continuously improving the quality of processes and products has become key to strategic business planning. The development and implementation of process monitoring and adjustment are

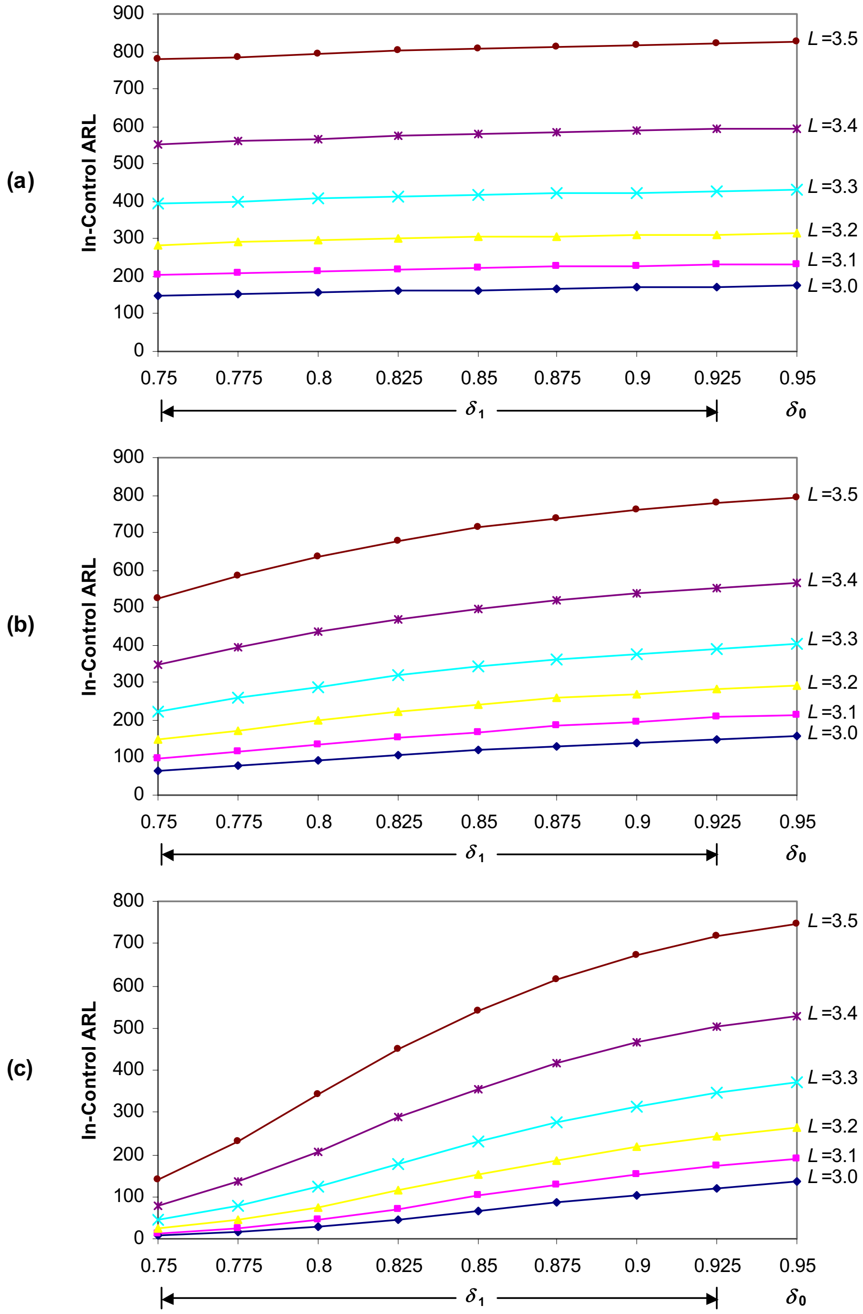

Figure 6. In-control ARLs of the AEWMA procedure for transition magnitudes: (a) $M = 5$; (b) $M = 10$; and (c) $M = 15$

becoming even more valuable in achieving the necessary quality level. This paper presented a monitoring and adjustment methodology for process transitions. The methodology could potentially reduce material waste and non-productive buffer times that are commonly used in practice. It also bridges the gap between two distinct process levels and facilitates the continual application of control charts.

We considered the AEWMA procedure to shorten the transition period as a means of improving the transition operation. The sensitivity study of the AEWMA procedure for the altered transition profile reveals that it is

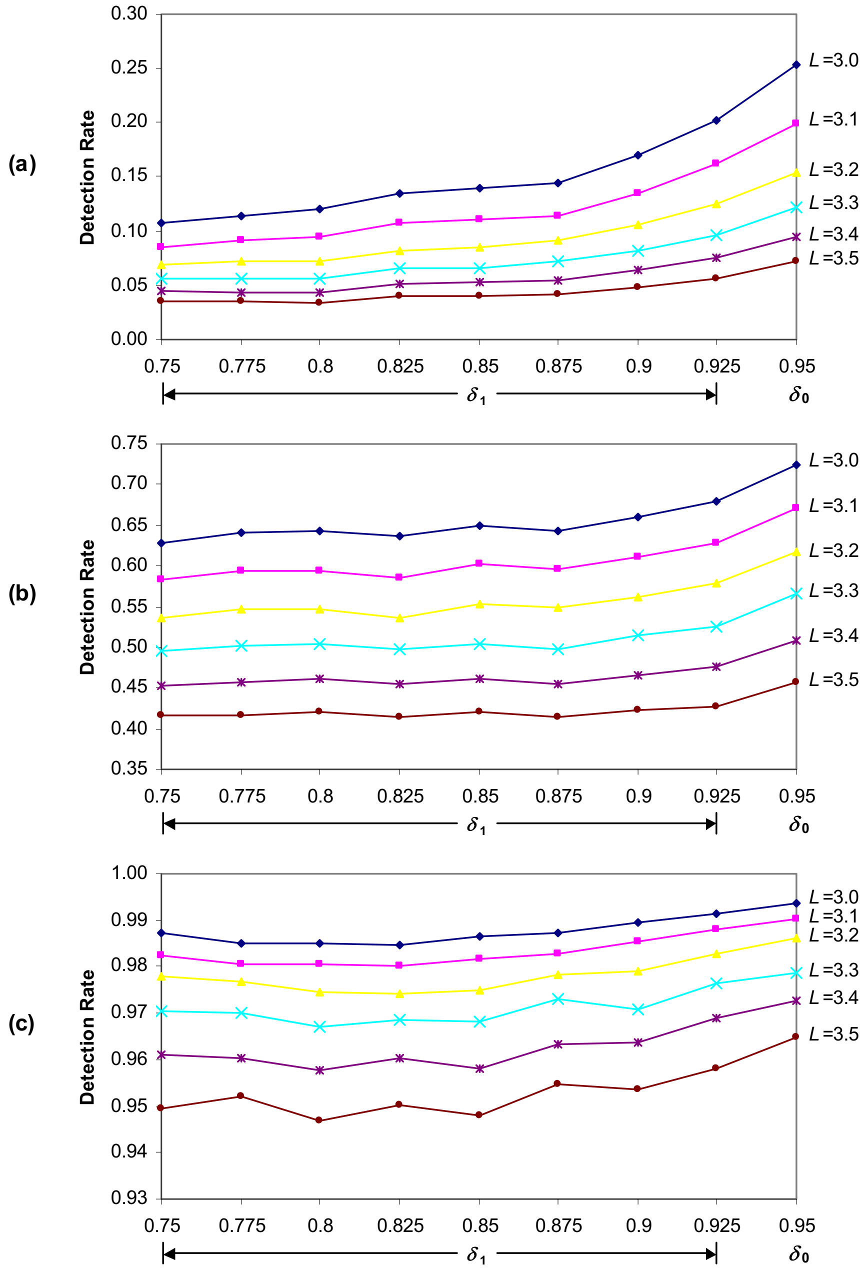

Figure 7. Detection rates of the AEWMA procedure for $M = 5$ and process shifts: (a) 1σ; (b) 3σ; and (c) 5σ

insensitive to transition adjustment when transition magnitudes are relatively small. To maintain a relatively small false alarm rate, we recommend using a control limit constant, L, greater than 3.1.

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