SECTION 4. Practitioner's corner

Jeffrey E. Jarrett (USA)

Perspectives on the quality movement in the supply chain environment

Abstract

The purpose of this paper is to introduce the demand for the quality movement practice in the supply chain environment. The author shows both the need and application of these measures, especially the need for multivariate quality concepts to reduce the costs of operating supply chains, to control the flow throughout the supply chain and in the dynamic behavior of supply chains, to utilize concepts associated with multivariate methods and autocorrelated time series.

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JEL Classification: C18, C19, C65, M10.

Introduction

Supply chain management involves the leveraging of channel wide integration to better serve customer needs. Increases in productivity and quality control and improvement will follow when firms will implement and coordinate quality management activities upstream. When corporate management recognizes the aspects of supply chain management, quality control and quality assurance two duties should be undertaken. The first refers to the process whereby measures are taken to make sure defective products and services are not part of the final output, and that the product design meets the quality standards set out at the initiation of the project. One may observe that quality assurance entails overlooking all aspects, including design, production, development, service, installation, as well as documentation. The quality movement is the field that ensures that management maintains the standards set and continually improves the quality of the output. According to Lee and Wang (2003, p. 26): *"The quality movement has offered us sound lessons that can be very powerful to address supply chain security lessons. Instead of final, end-product source inspection, the quality movement emphasizes prevention, total quality management, source inspection; profess control and a continuous improvement cycle. These are all ingredients for successful and effective ways to manage and mitigate the risks of supply chain security."*

We introduce the philosophy and methods of the quality improvement to achieve the best results of production and supply chain management. This paper focuses on supply chain planning with quality control in an environment with multiple manufacturing centers and multiple customers. We first discuss the needs for quality planning in the supply chain environment to focus on the notion of statistical process (or quality) control (SPC); why it is so vital to the performance of a firm's supply chain and why it is so vital to the performance of supply chains in the global firm environment? In turn, we introduce and discuss the desire for more sophisticated SPC to insure that quality and improvement is maintained in production processes involving more and greater sophisticated production methods.

While supply chains are so crucial to the health of business enterprises, these supply chains must be sustained by both preventative and emergency measures. Zhang, Yu and Huang (2009) propose several sophisticated strategies for dealing with SPC strategies in the supply chain environment. Their study presents principle agent models regarding the customer's quality evaluation and the supplier's quality prevention level decisions. Studies such as this may produce results not heretofore examined by the practioner's of SPC in the supply chain environment. In addition, threats to supply chains are real and many measures must be developed to indicate when supply chains are not operating in an efficient and productive manner. These measures include those of SPC which will indicate when risks are present in the supply chain. Since supply chains are increasingly globalized, these SPC measures must be appropriately placed in the supply chain and the choice of the particular SPC procedure is critical in developing an optimal plan.

1. Process control and improvement methodology

Most SPC methodologies assume a steady state process behavior where the influence of dynamic behavior is ignored. In the steady state system, dynamic behaviors are assumed not present and the focus is only on one variable at a time. Specifically, SPC control for changes in either the measure of location or dispersion or both. SPC procedures as practiced do disturb the flow of the production process and operations. In recent years, the use of SPC methodologies to address the process where behavior is characterized by more than one variable is emerging. The purpose of this next section is to review the basic univariate procedures to observe how they may be improved by more sophisticated methods having the same goal.

2. Univariate control charts

Shewhart control charts which is the central foundation of univariate SPC has one major shortcoming which we recognize now. The major drawback of the Shewhart chart is that it considers only the last data point and does not carry a memory of the previous data. As a result, small changes in the mean of a random variable are less likely to be detected rapidly. Exponentially weighted moving average (EWMA) chart improves upon the detection of small process shifts. Rapid detection of small changes in the quality characteristic of interest and ease of computations through recursive equations are some of the many good properties of the EWMA chart that make it attractive.

EWMA chart achieves faster detection of small changes in the mean. It is used extensively in time series modeling and forecasting for processes with gradual drift (Box and Draper, 1998). It provides a forecast of where the process will be in the next instance of time. It thus provides a mechanism for dynamic process control (Hunter, 1986).

The EWMA is a statistic for monitoring the process that averages the data in a way that gives exponentially less and less weight to data as they are further removed in time.

The EWMA statistic is defined by:

$$Z_i = \lambda \overline{X}_i + (1-\lambda) Z_{i-1} \quad with \quad 0 \le \lambda < 1, \quad Z_0 = \mu_0. \quad (1)$$

Can be used as the basis of a control chart. The procedure consists of plotting the EWMA statistic Z_i versus the sample number on a control chart with center line $CL = \mu_0$ and upper and lower control limits at

$$UCL = \mu_0 + k\sigma_{\bar{x}} \sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2i}\right]}, \quad (2)$$

$$LCL = \mu_0 + k\sigma_{\bar{x}} \sqrt{\frac{\lambda}{2-\lambda}\left[1-(1-\lambda)^{2i}\right]}. \quad (3)$$

The term $\left[1-(1-\lambda)^{2i}\right]$ approaches unity as i gets larger, so after several time periods, the control limit will approach steady state values.

$$UCL = \mu_0 + k\sigma_{\bar{x}} \sqrt{\frac{\lambda}{2-\lambda}}, \quad (4)$$

$$LCL = \mu_0 + k\sigma_{\bar{x}} \sqrt{\frac{\lambda}{2-\lambda}}. \quad (5)$$

The design parameters are the width of the control limits k and the EWMA parameter λ. Montgomery (2005) gives a table of recommended values for these parameters to achieve certain average run length performance.

In many situations, the sample size used for process control is $n = 1$; that is, the sample consists of an individual unit (Montgomery and Runger, 2003). In such situations, the individuals control chart is useful. The control chart for individuals uses the moving range of two successive observations to estimate the process variability. The moving range is defined as $MR_i = \text{abs}\,(X_i - X_{i-1})$ an estimate of $\hat{\sigma}$ is

$$\hat{\sigma} = \frac{\overline{MR}}{d_2} = \overline{MR}/1.128, \quad (6)$$

because $d_2 = 1.128$ when two consecutive observations are used to calculate a moving range. It is also possible to establish a control chart on the moving range using D_3 and D_4 for $n = 2$. The parameters for these charts are defined as follows.

The central line (CL) upper and lower control limits for a control chart for individual are:

$$UCL = \overline{X} + 3\overline{MR - d_2} = \overline{X} + 3\frac{\overline{MR}}{1.128},$$

$$CL = \overline{X}$$

and $$LCL = \overline{X} - 3\overline{MR/d_2} = \overline{X} - 3\overline{MR}1.128. \quad (7)$$

For a control chart for moving ranges

$$UCL = D_4\overline{MR} = 3.267\overline{MR},$$

$$CL = \overline{MR},$$

$$UCL = D_3\overline{MR} = 0. \quad (8)$$

Although very useful, more recent studies indicate that misplaced control limits are present in many applications as discussed in the next section.

3. Process with dynamic inputs and behavior

In an extensive survey, Alwan and Roberts (1995) found that more than 85% of industrial process control applications resulted in charts with possibly misplaced control limits. In many instances, the misplaced control limits result from autocorrelation of the process observations, which violates a basic assumption often associated with the Shewhart chart (Woodall, 2000). Autocorrelation of process observations has been reported in many industries, including cast steel (Alwan, 1992), blast furnace operations (Notohardjono and Ermer, 1986), wastewater treatment plants (Berthouex, Hunter, and Pallesen, 1978), chemical processes industries (Montgomery and Mastrangelo, 1991), semiconductor manufacturing (Kim and May, 1994), injection molding (Smith, 1993), applications with calibration curves (Mestek, Pavlik, and Suchanek, 1994), beer demand (Koksalan, Erkip, and Moskowitz, 1999) and basic rolling operations (Xia, Rao, Shan and Shu, 1994).

Several models have been proposed to monitor processes with autocorrelated observations. Alwan and Roberts (1988) suggest using an autoregressive integrated moving average (ARIMA) residuals chart, which they referred to as a special cause chart. For subsample control applications, Alwan and Radson (1992) describe a fixed limit control chart, where the original observations are plotted with control limit distances determined by the variance of the subsample mean series. Montgomery and Mastrangelo (1991) use an adaptive exponentially weighted moving average (EWMA) centerline approach, where the control limits are adaptive in nature and are determined by smoothed estimate process variability. Lu and Reynolds (1999) investigate the steady state average run length of cumulative sum (CUSUM), EWMA, and Shewhart control charts for autocorrelated data modeled as a first order autoregressive process plus an additional random error term. Last, Box and Luceno (1997) considering quality monitoring by feedback adjustment.

A problem with all these control models is that the estimate of the process variance is sensitive to outliers. If assignable causes are present in the data used to fit the model, the model may be incorrectly identified and the estimators of model parameters may be biased, resulting in loose or invalid control limits (Boyles, 2000). To justify the use of these methods, researchers have made the assumption that a period of "clean data" exists to estimate control limits. Therefore, methods are needed to assure that parameter estimates are free of contamination from assignable causes of variation. Intervention analysis, with an iterative identification of outliers, has been proposed for this purpose. The reader interested in more detail should see Alwan (2000, pp. 301-307), Atienza, Tang and Ang (1998), and Box, Jenkins, and Reinsel (1994, pp. 473-474; 2008). Atienza, Tang, and Ang (1998) recommend the use of a control procedure based on an intervention test statistic, λ, and show that their procedure is more sensitive than ARIMA residual charts for process applications with high levels of positive autocorrelation. They limit their investigation of intervention analysis, however, to the detection of a single level disturbance in a process with high levels of first order autocorrelation. Wright, Booth, and Hu (2001) propose a joint estimation method capable of detecting outliers in an autocorrelated process where the data available is limited to as few as 9 to 25 process observations. Since intervention analysis is crucial to model identification and estimation, we investigate varying levels of autocorrelation, autoregressive and moving average processes, different types of disturbances, and multiple process disturbances.

The ARIMA and intervention models are appropriate for autocorrelated processes which input streams are closely controlled. However, there are quality applications, which we refer to as "dynamic input processes," where this is not a valid assumption. The treatment of wastewater is one example of a dynamic process that must accommodate highly fluctuating input conditions. In the health care sector, the modeling of emergency room service must also deal with highly variable inputs. The dynamic nature of the input creates an additional source of variability in the system, namely the time series structure of the process input. For these applications, modeling the dynamic relationship between process inputs and outputs can be used to obtain improved process monitoring and control as discussed by Alwan (2000, pp. 675-679).

4. Transfer function modeling

West, Delana and Jarrett (2002) proposed the following transfer function model to solve problems having dynamic behavior.

If a process quality characteristic z_t, has a time series structure, an ARIMA model of the following general form can represent the undisturbed or natural process variation:

$$\Phi(B)a(B)z_t = \Theta(B)a_t. \tag{9}$$

In equation (1), B represents the back-shift operator, where $B(z_t) = z_{t-1}$. The value of $\Phi(B)$ represents the polynomial expression $(1 - \Phi_1(B) - \ldots - \Phi_1 B^p)$, which models the autoregressive (AR) structure of the time series. The value of the Θ (B) represents the polynomial $(1 - \Theta_1(B)$ - … - $\Theta_q B^q)$, which models the moving average (MA) structure of the time series. The value of $a(B)$ represents the expression $(1-B)_1^d(1-B^8)_2^d$, where $d = d_1 + sd_2$. This quantity is a polynomial in B that expresses the degree of differencing required to achieve a stationary series and accounts for any seasonal pattern in the time series. Finally, a_t is a white noise series with distribution N $(O,_\alpha^2)$. This model is described by Chen and Liu (1993a, 1993b). If the series z_t are contaminated by periods of external disturbances to the process, the ARIMA model may be incorrectly specified, the variability of the residuals overestimated, and the resulting control limits incorrectly placed.

The following transfer function model of Box and Tiao (1975) describes the observed quality characteristic, y_t, as a function of three courses of variability:

$$y_t = v(B)x_{t-b} + \frac{w(B)}{\delta(B)}I_t + \frac{(B)}{(B)}\alpha_t. \quad (10)$$

The first term $v(B)x_{t-b}$, is the dynamic input term and represents an impulse function. $v(B)$, applied to the input x_{t-b} with a lag of b time periods. If a dynamic relationship between the input and output time series exists, lagged values of process inputs can be modeled, resulting in considerable reduction of unexplained variance. The second term, $w(B)/\delta(B)I_t$, is the intervention term and identifies periods of time when assignable causes are present in the process. Here, I_t is an indicator variable with a value of zero when the process is undisturbed and a value of one when a disturbance is present in the process. See, for example, Box, Jenkins and Reinsel (1994, p. 392; 2008) for the development of the transfer function term, and Box, Jenkins and Reinsel (1994, p. 462; 2008) for details of the intervention term. The rational coefficient term I_t is a ratio of polynomials that defines the nature of the disturbance as detailed in Box, Jenkins and Reinsel (1994, p. 464; 2008). The third term $(\Theta(B)/\Phi(B)\ a_t$, is the basic ARIMA model of the undisturbed process from equation (9). We refer to equation (10) as the "transfer function" model throughout this paper.

Different types of disturbances can be modeled by the proper design of the intervention term. The two most common disturbances for quality applications are a point disturbance, with an impact observed for only a single time period, and a step disturbance, with an impact persisting undiminished through several subsequent observations. The point disturbance is modeled as an additive outlier (AO). An AO impacts the observed process at one observation. The AO is modeled in the form:

$$\frac{w(B)}{\delta(B)} = w_0, \quad (11)$$

where w_0 is a constant. A step disturbance to the process is modeled as a level-shift outlier (a form of innovational outlier or IO) in the form:

$$\frac{w(B)}{\delta(B)} = \frac{w_0}{1-B}. \quad (12)$$

Chang, Tiao, and Chen (1988) and Chen and Liu (1993a; 1993b) discuss both types of disturbance.

Chang, Tiao, and Chen (1988) extended the concepts of Box and Tiao (1975) to an iterative method for detecting the location and nature of outliers at unknown points in the time series. The above researchers defined procedures for detecting innovational outliers and additive outliers and for jointly estimating time series parameters. Their work also demonstrates the need for future study of the nature of outliers.

5. Multivariate control charts

Multivariate analyses utilize the additional information due to the relationships among the variables and these concepts may be used to develop more efficient control charts than simultaneously operated several univariate control charts. The most popular multivariate SPC charts are the Hotelling's T^2 (see Sullivan and Woodall (1996) and multivariate exponentially weighted moving average (MEWMA) (Elsayed and Zhang, 2007). Multivariate control chart for process mean is based heavily upon *Hotelling's* T^2 distribution, which was introduced by Hotelling (1947). Other approaches, such as a control ellipse for two related variables and the method of principal components, are introduced by Jackson (1956) and Jackson 1959. A straightforward multivariate extension of the univariate EWMA control chart was first introduced in Lowry Woodall, Champ and Rigdon (1992) and Lowry and Montgomery (1995) developed a multivariate EWMA (MEWMA) control chart. It is an extension to the univariate EWMA.

$$Z_i = \Lambda\, \overline{X} + (I - \Lambda)Z_{i-1}, \quad (13)$$

where I is the identity matrix, Z is the ith EWMA vector, $\overline{X}$, is the average ith observation vector I = 1, 2, …, n, Λ is the weighting matrix. The plotting statistic is:

$$T_i^2 = Z_i \, \Sigma_{zi}^{-1} \, Z_i. \quad (14)$$

Lowry and Montgomery (1995) showed that the $(k,1)$ element of the covariance matrix of the ith EWMA, $\sum_{zi}$, is:

$$\sum zi(k,1) = \lambda_k \lambda_1 \frac{[1-(1-\lambda_k)^{I}(1-\lambda_1)^{i}]}{[\lambda_k + \lambda_1 - \lambda_k\lambda_1]} \boldsymbol{\sigma}_{k,1}, \quad (15)$$

where $\sigma_{k,1}$ is the $(k,1)$ element of $\sum$, the covariance matris of $\overline{X}$.

If $\lambda_1 = \lambda_2 = \ldots\ldots = \lambda_p = \lambda$, then the above expression simplifies to:

$$\sum zi(k,1) = \frac{\lambda}{2-\lambda}[1-(1-\lambda)^{2i}]\sum, \quad (16)$$

where $\sum$ is the covariance matrix of the input data.

There is a further simplification. When I becomes large, the covariance matrix may be expressed as:

$$\sum zi = \frac{\lambda}{2-\lambda}\sum. \quad (17)$$

Montgomery and Wadsworth (1972) suggested a multivariate control chart for process dispersion based

$$UCL = (|S|1b_1)(b_1 + 3b_2^{\ 1/2}),$$

$$CL = |S|, \quad (18)$$

$$UCL = (|S|1b_1)(b_1 + 3b_2{}^{1/2}),$$

where $b_1 = [1/(n-1)^p \prod_{i=1}^{P} (n-1),$ (19)

and $b_2 = [1/(n-1)^{2P}] \prod_{i=1}^{P} (n-1)[\prod_{j=1}^{P} (n-j+2) - \prod_{j=1}^{P} (n-j).$ (20)

In the next section, we explore how multivariate methods improve process control in the supply chain.

6. Interpretation of multivariate process control

Multivariate quality control (MPC) charts (Hotelling, 1947; Jackson, 1956, 1959, 1985; Hawkins, 1991, 1993, Kalagonda and Kulkarni, 2003, 2004; Wierda, 1994; Jarrett and Pan, 2006, 2007a, 2007b; Mestik, Mastrangelo and Forrest, 2002) have several advantages over creating multiple univariate charts for the same business situation:

1. The actual control region of the related variables is represented. In the bivariate case the representation is elliptical.
2. You can maintain a specific probability of a Type 1 error (the risk).
3. The determination of whether the process is out of or in control is a single control limit.

Currently, there is a gap between theory and practice and this is the subject of this manuscript. Many practitioners and decision-makers have difficulty interpreting multivariate process control applications, although Montgomery (2005) addresses many of the problems of understanding not discussed in the technical literature noted before. For example, the scale on multivariate charts is unrelated to the scale of any of the variables, and an out-of-control signal does not reveal which variable (or combination of variables) causes the signal.

Often one determines whether to use a univariate or multivariate chart by constructing and interpreting a correlation matrix of the pertinent variables. If the correlation coefficients are greater than 0.1, you can assume the variables correlate, and it is appropriate to construct a multivariate quality control chart.

The development of information technology enables the collection of large-size data bases with high dimensions and short sampling time intervals at low cost. Computational complexity is now relatively simple for on-line computer-aided processes. In turn, monitoring results by automatic procedures produces a new focus for quality management. The new focus is on fitting the new environment. SPC now requires methods to monitor multivariate and serially correlated processes existing in new industrial practice.

Illustrations of processes which are both multivariate and serially correlated are numerous in the production of industrial gasses, silicon chips and highly technical computer driven products and accessories. In optical communication products manufacturing, the production of fiber optic is based on SiO_2 rods made from condensation of silicon and oxygen gasses. The preparation of SiO_2 rods need to monitor variables such as temperature, pressure, densities of different components, and the intensity of molecular beams. Similar processes exist in chemical and semiconductor industries where materials are prepared and made. In service industries, the correlation among processes are serial because due to the inertia of human behaviors, and also cross-sectional because of the interactions among various human actions and activities. As an example, the number of visits to a restaurant at a tourist attraction may be serially dependent and also related to (1) the room occupation percentage of nearby overnight residences and (2) the cost and convenience of transportation. Furthermore, the latter factors are also autocorrelated and cross-sectionally correlated to each other. Business management and span of control problems relate unit sales to internal economic factors such as inventory, accounts receivable, labor and materials costs, and environmental factors such as outputs, competitors' prices, specific demands, and the relevant economy in general. These problems are multivariate and serially correlated because one factor at one point in time is associated with other factors at other points in time (past, present and future).

SPC emphasizes the properties of control for decision making while it ignores the complex issues of process parameter estimation. Estimation is less important for Shewhart control charts for serially independent processes because the effects of different estimators of process parameters are nearly indifferent to the criterion of *average run length* (ARL). Processes' having serial correlation, estimation becomes the key to correct construction of control charts. Adopting workable estimators is then an important issue.

In the past, researchers studied SPC for serially correlated processes and SPC for multivariate processes separately. Research on quality control charts for correlated processes focused on univariate processes. Box, Jenkins, and Macgregor (1974) and Berthouex, Hunter and Pallesen (1978) noticed and discussed the correlated observations in production processes. Alwan and Roberts (1988) proposed a general approach to monitor residuals of univariate autocorrelated time series where the systematic patterns are filtered out and the special changes are more exposed. Other studies include Montgomery and Friedman (1989), Harris and Ross (1991), Montgomery and Mastrangelo (1991), Maragah and

Woodall (1992), Wardell, Moskowitz and Plante (1994), Lu and Reynolds (1999), West, Delana and Jarrett (2002) and West and Jarrett (2004), English and Sastri (1990), Pan and Jarrett (2004) suggested *state space methodology* for the control of auto correlated process. Further, additional technologies implemented by Testik (2005), Yang and Rahim (2005) and Yeh, Huang and Wu (2004) provide newer methods for enabling better MPC methods.

In Alwan and Roberts' approach, a time series is separated into two parts that are monitored in two charts. One is the common-cause chart and the other is the special-cause chart. The common cause chart essentially accounts for the process's systematic variation that is represented by an autoregressive-integrated-moving-average (ARIMA) model, while the special cause chart is for detecting assignable causes that can be assigned in the residual of the ARIMA model. That is, the special cause chart is designed as Shewhart-type chart to monitor the residuals filtered and whitened from the autocorrelated process (with certain or estimated parameters). In this analysis, the authors suggest methods used in conventional quality control software (i.e., *Minitab*®). These methods entitled multivariate T^2 and Generalized Variance control charts. These multivariate charts show how several variables jointly influence a process or outcome. For example, you can use multivariate control charts to investigate how the tensile strength and diameter of a fiber affect the quality of fabric or any similar application. If the data include correlated variables, the use of separate control charts is misleading because the variables jointly affect the process. If you use separate univariate control charts in a multivariate situation, Type I error and the probability of a point correctly plotting in control are not equal to their expected values. The distortion of these values increases with the number of measurement variables.

Multivariate control charting has several advantages over creating multiple univariate charts:

- The actual control region of the related variables is represented (elliptical for bivariate case).
- You can maintain a specific Type 1 error.
- A single control limit determines whether the process is in control.

Conclusions

This paper discusses the control chart usage and illustrate why better procedures are available to supply chain managers. For example, we illustrated methods developed by Alwan and Roberts' utilizing residual chart analysis. Later we explored methods such as West et al. transfer function application and traditional Multivariate Hotelling T^2 chart to monitor multivariate and multivariate serially correlated processes (those with dynamic inputs). The scheme can be viewed as a generalization of Alwan and Roberts' special cause approach to multivariate cases. The guideline and procedures of the construction of VAR residual charts are detailed in this paper. Molnau et al. (2001) produces a method for calculating ARL for multivariate exponentially weighted moving average charts (2001). Mastrangelo and Forrest (2002) simulated a VAR process for SPC purposes. However, the general study on VAR residual charts is heretofore not reported. In addition, more recent studies by Kalagonda and Kulkarni (2003, 2004), and Jarrett and Pan, (2006, 2007a, 2007b) indicate additional ways in which one can improve upon the multivariate methods currently available in commercial quality control software such as *Minitab*® and others. These newer techniques provide more statistically accurate and efficient methods for determining when processes are in or not control in the multivariate environment. When these methods become commercially available, practitioners should be able to implant these new statistical algorithms for multivariate process control charts (MPC) using ARL measure to control and improve output.

These new methods provide methods for MPC charts focusing on the average run length. The purpose is to indicate how useful these techniques are in the supply chain environment where processes are multivariate, dynamic or both. Simple SPC charts though very useful in simple environments may have limited use in the supply chain. In any event, future research should focus on exploring the characteristics of the supply chain and finding the best model to implement quality planning and improvement programs. Multivariate analysis should provide many of the new tools for adaption in improving supply chain management. The costs of security, stoppages and threats to the supply chain will diminish when managers explore the usefulness of multivariate methods noted before. Last, these supply managers much be trained, retrained and continually trained in those methods that best fit the supply chain environment. Simple Shewhart methods no longer are sufficient to manage in the global environment of the supply chain. In the future, I suspect as supply become more global some of the underlying mathematics of modeling will also seek to handle more difficult problems when extreme value occur. Knowledge of extreme value theory (EVT) will become very useful in predicting and accounting distribution of data having long and heavy tails in their distributions (see Novak (2012) for the mathematical underpinning of predicting and accounting for extreme values).

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