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Process Control, the Bull Whip Effect and the Supply Chain

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Abstract

The purpose is to introduce the demand for statistical quality control practice in the supply chain environment. We show 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 auto correlated variables. We note that the quality output is as important as the “bull whip” efficiency in the supply chain.

Keywords: Supply Chain, “Bull Whip”, Quality Control and Improvement, Multivariate Methods, Auto correlated Data.

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 implement and coordinate quality management activities upstream. We introduce the philosophy and methods of statistical quality control (SQC and or Statistical Process Control (SPC)) and 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 where the methodology of SQC fits and why it is so vital to the performance of the supply chain. Supply chains contain many multi-correlated variables with dynamic inputs especially in the expanding global environment.

While supply chains are so crucial to the health of business enterprises, these supply chains must be sustained by both preventative and emergency measures. Threats to supply chains are real and many and measures must be developed to indicate when supply chains are not operating in an efficient and productive manner. For example, the “bull whip” effect refers to the phenomenon of demand distortion in a supply chain [1]. Developed a control technique based on a divergence system to reduce the “bull-whip” effect in a single product supply chain. In addition, the divergence-based control strategy applies to stabilize the supply chain dynamics with a considerable reduction in total costs. These applications which include those of SQC will indicate when risks are present in the supply chain and reduce costs, bottlenecks and inventory shortages. Since supply chains are increasingly globalized, these SQC measures must be appropriately placed in the supply chain and the choice of the particular SQC procedure is critical in developing an optimal plan to control and improve product and services.

In addition, others studying the effects of the recent downturn in economic activity offered research on the “bull whip” effect and how management can react to it. Stated differently does management have the tools to react to create counter-strategies to “tame” the bullwhip? Lee [2] introduced this discussion with examples from Cisco, Kimberly-Clark and other corporations. Dooley et al. [3] researched methods to control and improve inventory methods to react to the volatile changes in orders and inventories. They found that firms responded with different operational strategies to the recession of 2008. Over response was exhibited by many firms in their study indicating the need and desires to control and improve management methods. We propose methods to analyze data and to seek information from data to react to

supply chain effects. Analysis by methods proposed in this study will enable those who manage supply chains to react more efficiently and recognize when supply chains are changing.

Quality Control and Improvement Methodology

Most SQC 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 the control of only one variable at a time. Specifically, SQC control for changes in either the measure of location or dispersion or both. SQC procedures as practiced do disturb the flow of the production process and operations. In recent years, the use of SQC methodologies to address the process where behavior is characterized by more than one variable is emerging. We, thus, begin by considering steady state methods and later expand the discussion to the development of multivariate methods having dynamic processes.

Univariate Control Charts

One major drawback of the Shewhart Control charts 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) control charts improve 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 was first introduced by Alwan and Roberts [4] to achieve faster detection of small changes in the mean. The EWMA chart is used extensively in time series modeling and forecasting for processes with gradual drift [5]. 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 [6].

The (EWMA) is a statistic for monitoring the process that averages

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the data in a way that gives exponentially less and less weight to data as they are further removed in time.

The Exponentially Weighted Moving Average (EWMA) defined as

$$Z_i = \lambda \bar{X}_i + (1-\lambda)Z_{i-1} \text{ with } 0 \leq \lambda < 1, Z_0 = \mu_0 \tag{1}$$

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

$$UCL = \mu_0 + k\hat{\sigma} \bar{x} \sqrt{\frac{\lambda}{2-\lambda} [1-(1-\lambda)2i]} \tag{2}$$

$$LCL = \mu_0 - k\hat{\sigma} \bar{x} \sqrt{\frac{\lambda}{2-\lambda} [1-(1-\lambda)2i]} \tag{3}$$

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

$$UCL = \mu_0 + k\hat{\sigma} \bar{x} \sqrt{\frac{\lambda}{2-\lambda}} \tag{4}$$

$$LCL = \mu_0 - k\hat{\sigma} \bar{x} \sqrt{\frac{\lambda}{2-\lambda}} \tag{5}$$

The design parameters are the width of the control limits k and the EWMA parameter λ . Montgomery [7] 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 [8] 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 $MR_i = |X_i - X_{i-1}|$ an estimate of σ is

$$\hat{\sigma} = \frac{MR}{1.128} \tag{6}$$

$$d_2 = 1.128$$

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 D3 and D4 for $n = 2$.

The parameters for these charts are defined as follows

The center line and upper and lower control limits for a control chart for individual are

$$UCL = \bar{X} + 3\overline{MR} = \bar{X} + 3\overline{MR}CL = \bar{X}LCL = \bar{X} - 3\overline{MR} = \bar{X} - 3\overline{MR} \tag{7}$$

$$d_2 = 1.128$$

And for a control chart for moving ranges

$$UCL = D4\overline{MR} = 3.267\overline{MR}$$

$$CL = \overline{MR} \tag{8}$$

$$LCL = D3\overline{MR} = 0$$

Without going into specific computer software, the author utilized many such software, Minitab, SAS and others and perform extremely well from the view of ease of software use and contain the algorithms noted above. The ease of use is enhanced by wonderful tutorials for illustration of use.

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 SQC charts are the Hotelling's T2 and multivariate exponentially weighted moving average (MEWMA) (Elsayed and Zhang) [9]. Multivariate control chart for process mean is based heavily upon Hotelling's T2 distribution, which was introduced by Hotelling [10]. Other approaches, such as a control ellipse for two related variables and the method of principal components, are introduced by Jackson [11-13].

Lowery and Montgomery [14]. introduced a straightforward multivariate extension of the Univariate EWMA control chart was first introduced earlier by Lowry et al. [15]. They developed a multivariate EWMA (MEWMA) control chart. It is an extension to the Univariate EWMA.

$$Z_i = \Lambda \bar{X}_i + (I - \Lambda)Z_{i-1} \tag{9}$$

Where I is the identity matrix, Z_i is the i th EWMA vector, \bar{X}_i is the average i th observation vector $I = 1, 2, \dots, n$, Λ is the weighting matrix. The plotting statistic is

$$Ti2 = Z_i \sum_{z_i}^{-1} Z_i \tag{10}$$

Lowry, et al. [15] Indicated that the $(k, 1)$ element of the covariance matrix of the i th EWMA, $\sum Z_i$ is

$$\sum Z_i (k,1) = \lambda k \lambda 1 [1 - (1 - \lambda k)I (1 - \lambda I)^i] \hat{\sigma} k,1 \tag{11}$$

$$[\lambda k + \lambda 1 - \lambda k \lambda 1]$$

where $\hat{\sigma} k,1$ is the $(k,1)$ element of Σ , the covariance matrix over the \bar{X} 's.

If $\lambda 1 = \lambda 2 = \dots = \lambda p = \lambda$ then the above expression simplifies to

$$\sum Z_i (k,1) = \frac{\lambda}{2-\lambda} [1 - (1-\lambda)2i] \Sigma \tag{12}$$

where Σ is the covariance matrix of the input data.

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

$$\sum z_i = \frac{\lambda}{2-\lambda} \Sigma \tag{13}$$

Montgomery and Wadsworth [16]. suggested a multivariate control chart for process dispersion based procedures

$$UCL = (|S|b1) (b1 + 3b2 \frac{1}{2})$$

$$CL = |S| \tag{14}$$

$$UCL = (|S|b1) (b1 + 3b2 \frac{1}{2})$$

$$\text{where } b1 = [1/(n-1)]^p \prod_{i=1}^{n-1} (n-i) \tag{15}$$

$$\text{and } b2 = [1/(n-1) 2P] \prod_{i=1}^{n-1} (n-i) [\prod_{j=1}^P (n-j+2) - \prod_{j=1}^P (n-j)] \tag{16}$$

Interpretation of Multivariate Process Control

Multivariate quality control (MPC) charts [10-13,17-21] have several advantages over creating multiple Univariate charts for the same business situation. The actual control region of the related variables is represented. In the bivariate case the representation is elliptical. You can maintain a specific probability of a Type 1 error (the α risk). 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 the book by Montgomery [7] 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). For implementation within the structure of the supply chain, Jarrett [22] show how the quality movement uses sophisticated SQC methods within the context of the supply. The conclusion is that supply chains achieve maximum speed, utility and quality with the merging of quality control and improvement methods in the supply chain to achieve the "bull whip" effect.

In turn, 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 and are statistically significant, 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. SQC 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 and optical communication products manufacturing, the production of fiber optic is based on SiO₂ rods made from condensation of silicon and oxygen gasses. The preparation of SiO₂ rods need to monitor variables such as temperature, pressure, densities of different components, and the intensity of molecular beams. They are often important and manageable in biomedical tests as well [23]. 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 auto correlated and cross-sectional correlated variables. 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).

SQC 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 SQC for serially correlated processes and SQC for multivariate processes separately. Research on quality control charts for correlated processes focused on Univariate processes. Berthouex, Hunter and Pallesen [24] noticed and discussed the correlated observations in production processes. Alwan and Roberts [4] proposed a general approach to monitor residuals of univariate auto correlated time series where the systematic patterns are filtered out and the special changes are more exposed. Other studies include Harris and Ross, Montgomery and Mastrangelo, Maragah and Woodall, Wardell, Moskowitz and Plante, Lu and Reynolds, West, Delana and Jarrett and West and Jarrett, English and Sastri, Pan and Jarrett [25-33] suggested state space methodology for the control of auto correlated process. Further, additional technologies implemented by Yang and Rahim and Yeh et al. [34,35] provide newer methods for enabling better MPC methods.

In Alwan and Roberts' [4] 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 auto correlated process (with certain or estimated parameters). In this analysis, the authors suggest methods used in conventional quality control software (i.e., Minitab) entitled multivariate T2 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. Since multivariate control charting has several advantages over creating multiple univariate charts as noted earlier, let us now consider these methodologies with processes containing dynamic inputs which often characterize a global supply chain environment.

Process with Dynamic Inputs and Behavior

In an extensive survey, Alwan and Roberts [36] 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 Control chart. Autocorrelation of process observations has been reported in many industries, including cast steel [37], blast furnace operations wastewater treatment plants [24], chemical processes industries [26], semiconductor manufacturing injection molding and basic rolling operations.

Several models have been proposed to monitor processes with auto correlated observations. Alwan and Roberts [4] suggest using an autoregressive integrated moving average (ARIMA) residuals chart, which they referred to as a special cause chart. For subsample control applications, Alwan [37] 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 [26] use an adaptive exponentially weighted moving average (EWMA) centerline approach, where the control limits are adaptive in nature and determined by a smoothed estimate process variability. Lu and Reynolds [29] investigate the steady state average run length of cumulative sum (CUSUM), EWMA, and Shewhart control charts for auto correlated data modeled as a first order autoregressive process plus an additional random error term.

A problem with all these control models is that the estimate of the process variance is sensitive to outliers which is especially import in supply chain applications. 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 [38]. 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 [5,39] 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 [40] propose a joint estimation method capable of detecting outliers in an auto correlated 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 auto correlated processes whose 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 [41].

Transfer Function Modeling

West, Delana and Jarrett [30] 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.

$$\Phi(B) a(B) z_t = \theta(B) a_t \tag{17}$$

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 $(1 - \Phi_1 B - \dots - \Phi_1 B^p)$, which models the autoregressive (AR) structure of the time series. The value of the $\Theta(B)$ represents the polynomial $(1 - \Theta_1 B - \dots - \Theta_q B^q)$, which models the moving average (MA) structure of the time series. The value of $a(B)$ represents the expression $(1 - B)^d (1 - B^s)^2$, where $d = d_1 + s d_2$. 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 $N(0, \sigma_a^2)$. This model is described by Chen and Liu [43-47]. If the series z_t is 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 describes the observed quality characteristic, y_t , as a function of three courses of variability:

$$y_t = v(B) x_{t-b} + \frac{w(B)}{\delta(B)} I_t + \frac{\theta(B)}{\phi(B)} a_t \tag{18}$$

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, [5] for the development of the transfer function term, and [5] for details of the intervention term. The rational coefficient term if it is a ratio of polynomials that defines the nature of the disturbance as detailed in [5]. The third term $(\theta(B)/\phi(B))a_t$, is the basic ARIMA model of the undisturbed process from Equation (17). We refer to Equation (18) 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

$$\frac{w(B)}{\delta(B)} = w_o \tag{19}$$

where w_o 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.

$$\frac{w(B)}{\delta(B)} = \frac{W_o}{1-B} \tag{20}$$

Chang, Tiao, and Chen and Chen and Liu [42,43] discussed both types of disturbance. Chang, Tiao, and Chen extended the concepts of Box and Tiao [42,44] to an iterative method for detecting the location and nature of outliers at unknown points in the time series. This last method by defining a procedure for detecting innovational outliers and additive outliers and for jointly estimating time series parameters initially demonstrate additional possibilities for achieving quality and improvement in the supply chain.

Conclusions

In this study we outlined those procedures in SQC both Univariate and Multivariate, both exponential and not exponential with their various attributes and indicate how the bull whip effect of supply chains can only be enhance by the integration of quality and process

control methods. Stated differently, we propose that the supply chain be integrated at every stage with the quality movement to produce finish products or services which are economically efficient, quick and least time spent on fixing product or service for malfunctioning processes.

This manuscript emphasizes the discussion started by Alwan and Roberts' residual chart, West et. al. transfer function application and traditional Multivariate Hotelling T2 chart to monitor multivariate and multivariate serially correlated processes (those with dynamic inputs). Many examples exist which generalize the 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. [45] produces a method for calculating average run length (ARL) for multivariate exponentially weighted moving average charts. Mastrangelo and Forrest [46] simulated a VAR process for statistical process control SQC purposes. However, the general study on VAR residual charts is heretofore not reported. In addition, more recent studies by Kalagonda and Kulkarni [17,18], and Jarrett and Pan, [19-21] indicate additional ways in which one can improve upon the multivariate methods currently available in commercial quality control software such as Minitab® and SAS®. These newer techniques provide more statistically accurate and efficient methods for determining when processes are in or not control in the multivariate environment. These methods are commercially available, so practitioners should be able to implant these new statistical algorithms for MPC charts which shall be of great use in the environment of the global supply chain.

These advanced and multivariate methods provide for MPC charts focusing on the average run length (ARL). The purpose is to indicate how useful these techniques are in the supply chain environment where processes are multivariate, dynamic or both. Simple Shewhart Control 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 among many to implement quality planning and improvement programs. In addition, one expects that criteria other than ARL will be the focus of research in multivariate quality methods. They may even quicken the effects of the "bull whip."

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