The Quality Movement in the Supply Chain Environment

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The purpose of this paper is to introduce the demand for the quality movement practice in the supply chain environment. 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 will be shown. The purpose is to reduce costs in the supply chain system and improve the probability of meeting the "due time."

Supply chain management involves the leveraging of channel-wide integration to better serve customer needs. Increases in productivity, quality control, and improvement follow when firms implement and coordinate quality management activities upstream. When corporate management recognizes the aspects of supply chain management, quality control and quality assurance, two steps should then be taken. The first is 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 Whang (2003, p. 26):

> The quality movement has offered 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, process 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.

The philosophy and design of quality improvement is to achieve the best economic results of production and supply chain management. Stated differently, the goal of the quality movement is to reduce the expected total costs per unit in the supply chain system and increase the probability of meeting the “due time” without sacrificing the quality of the supplier’s output. This enables suppliers to fully satisfy their customers. This paper focuses on supply chain planning with quality control in an environment with multiple manufacturing centers and multiple customers. First addressed will be the needs for quality planning in the supply chain environment in order to focus on where the notion of statistical process (or quality) control (SPC) fits and why it is so vital to the performance of the supply chain environment in general and in a global environment. In turn, the desire for more sophisticated methods to ensure that quality and improvement are maintained in production processes involving more and greater sophisticated production methods will be discussed.

While supply chains are crucial to the health of business enterprises, these supply chains must be sustained by both preventative and emergency measures. Zhang, Yu, and Huang (2009) proposed several sophisticated strategies for dealing with SPC strategies in the supply chain environment. The study presented principle agent models regarding the customer’s quality evaluation and the supplier’s quality prevention level decisions. Studies such as this may have produced results not previously examined by the practitioners 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 to developing an optimal plan.

Furthermore, Sun, Tsubaki, and Matsui (2006) proposed control chart systems in the supply chain management system to improve the customer satisfaction of suppliers. The purpose was to show the mathematical foundation in order to study the relationships between univariate control chart limits and the expected total cost per unit time in the arrival of (due) time for the product in the supply chain. The study gave evidence as to the use of simple univariate control on how the process of SPC reduced shipping costs and made certain that due time for arrivals were met. The study was limited to simple control charts and did not address the important question of whether SPC systems could vary when simple control chart design was the basis of the system or if more sophisticated models for SPC systems should be utilized.

Quality Control and Improvement Methodology

In the twenty-first century, competition no longer relies on the economic efficiency of one economic entity versus another or others. The global environment requires managers to analyze the supply chain of one system versus the supply chain of other systems. Quality management, including SPC, is supposed to positively impact the supply chain in order to reduce the total costs of manufacturing and distribution and to meet the expectation of “end-of-the-line” customers who require that due dates be met and the product delivered is fit for use. This manuscript proposes that supply chain systems become more efficient by reducing costs of unfit products. This results in greater costs to both the suppliers and the customers in order to meet the constraints on the system by “due times.” Supply chain systems can also become more efficient as a result of a loss in faith from customers who depend on supplies, by using optimal production scheduling, and other methods for streamlining manufacturing and distribution.

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 to be present and the focus is on the control of only one variable at a time. Specifically, SPC controls for changes in either the measure of location or dispersion or both. SPC procedures as practiced do in fact 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 in order to see how they may be improved by more sophisticated methods while maintaining the same goal.

Univariate Control Charts

A Shewhart control chart which is the central foundation of univariate SPC has one recognized major shortcoming. 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 rapidly detected. An 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 properties of the EWMA chart that make it attractive (Appendix 1).

Although very useful, more recent studies indicated that misplaced control limits were present in many applications. These are the same methodologies commonly seen in quality management programs. For example Kuei, Madua, and Lin (2008) indicated that quality management practices were “closely associated” with better supply chain performance and greater capabilities. Flynn and Flynn (2005) also supported the desire for integration of quality management with supply chain management with empirical evidence. In addition, Kaynak and Hartly (2008) provided empirical data and analysis by statistical methods of the relationships between quality management and performance measures to further the improvement of customer relations and other constructs. Finally, Jarrett (2012) produced information that suggested that simple univariate control charts were often not the best method for quality management in the supply chain and managers should consider additional methods for the merging of quality management with supply chain management systems. Whereas EWMA charts may produce better control charts than simple univariate control charts, more sophisticated control charts will actually be easier to use and produce more efficient results.

Processes with Dynamic Inputs

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 Control Chart (Woodall, 2000). Autocorrelation of process observations has been reported in many industries, including cast steel (Alwan, 1992), blast furnace operations, wastewater treatment plants (Berthouex, Hunter, & Pallesen, 1978), chemical processes industries (Montgomery & Mastrangelo, 1991), semiconductor manufacturing (Kim & May, 1994), injection molding (Smith, 1993), and basic rolling operations (Xia et al., 1994).

Several models have been proposed to monitor processes with autocorrelated observations. Alwan and Roberts (1988) suggested using an autoregressive integrated moving average (ARIMA) residuals chart, which they referred to as a special cause chart. For subsample control applications, Alwan (1992) described a fixed limit control chart, where the original observations were plotted with control limit distances determined by the variance of the subsample mean series. Montgomery and Mastrangelo (1991) used an adaptive exponentially weighted moving average (EWMA) centerline approach, where the control limits were adaptive in nature and determined by a smoothed estimate process variability. Lu and Reynolds (2001) investigated 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 was that the estimate of the process variance was sensitive to outliers which is especially important in supply chain applications. If assignable causes present in the data are 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. Atienza, Tang, and Ang (1998) recommended the use of a control procedure based on an intervention test statistic, λ, and showed that the procedure was more sensitive than ARIMA residual charts for process applications with high levels of positive autocorrelation. The investigation of intervention analysis was limited, however, to the detection of a single level disturbance in a process with high levels of first order autocorrelation. Wright, Booth, and Hu (2001) proposed a joint estimation method capable of detecting outliers in an autocorrelated process where the data available was limited to as few as 9 to 25 process observations. Since intervention analysis is crucial to model identification and estimation, it is important to 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 whose input streams are closely controlled. However, there are quality applications, which are referred 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).

When processes violate the assumptions of simple univariate control charts, another method for SPC must be found (Woodall, 2000). Earlier it was pointed out that the placement of quality control limits (Sun & Matsui, 2008) caused changes in the expected total cost per unit in the supply and in the "due time" as well. Misplacement of control by simple control charts will have a greater effect on the economic efficiency of the supply chain management system. In turn, the implication is that if a manager does not recognize the dynamics of the SPC system, the consequential effect will likely be to make the prevailing supply chain system noncompetitive. If this is so, other SPC systems that should be utilized to make the supply chain system competitive should be examined. Lastly, a question remains as to whether the effect of reducing the cost of the supply and improvement in meeting the "due time" will be met by the Alwan and Roberts method. Since it has been noted that control limits of simple control charts correlated with goals, more efficient methods that reduce the likelihood of false signals from control charts will reduce the number of products requiring additional effort to rework nonconforming units. Thus, a manager can only expect to reduce costs and increase the probability of meeting "due time" requirements. One additional model proposed by West, Delana, and Jarrett (2002) followed a transfer function model to solve problems having dynamic behavior. The result was to design a SPC system to produce dynamic control charts that had control limits that did not violate the assumption of autocorrelation in the various time series of data. The model was based on a study by Chen and Liu (1993a, 1993b) and followed the transfer function model of Box and Tiao (1975). Specific applications of the last model were given by Box, Jenkins, and Reinsel (1994, 2008) for the development of the transfer function term and for details of the intervention term. Other examples can be seen in Chang, Tiao, and Chen (1988) who extended the model of Box and Tiao (1975). Also, Chen and Liu (1993a, 1993b) discussed both autocorrelation and intervention disturbances in time series. These modelers, defined procedures for detecting innovational and additive outliers and for jointly estimating time series parameters. The study also demonstrated the need for future studies of the nature of outliers. However, further research into the relation of these methods is needed for determining control chart limits and their correlation with the probability of meeting the "due time" requirement and minimizing the expected cost per unit in the supply chain when such disturbances arise.

Multivariate Control Charts (MPC)

Charts that have only one limit to determine signals as to whether the process is in control or not would be additionally beneficial to supply chain systems managers. By having a single control limit based on the *average run length* (ARL), one can determine more easily the ability to control the "due time" and the expected total supply chain costs.

A multivariate analysis utilizes the additional information of the relationships among the variables. 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 (Sullivan & Woodall, 1996) and a multivariate exponentially weighted moving average (MEWMA) (Elsayed & Zhang, 2007). Multivariate control chart for process mean is based heavily upon Hotelling's T^2 distribution (Hotelling, 1947). Other approaches, such as a control ellipse for two related variables and the method of principal components, were introduced by Jackson (1956, 1959). A straightforward multivariate extension of the univariate EWMA control chart was first introduced in Lowry et al. (1992) and Lowry and Montgomery (1995) developed a multivariate EWMA (MEWMA) control chart. It is an extension to the univariate EWMA.

Interpretation of Multivariate Process Control Charts

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

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

Currently, there is a gap between theory and practice. Many practitioners and decision-makers have difficulty interpreting multivariate process control applications, although the book by Montgomery (2005) addressed 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, it can be assumed 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 online computer-aided processes. In turn, monitoring results by automatic procedures produces a new focus for quality management. The new focus is on fitting with the new environment. SPC now requires methods to monitor multivariate and serially correlated processes existing in new industrial practices.

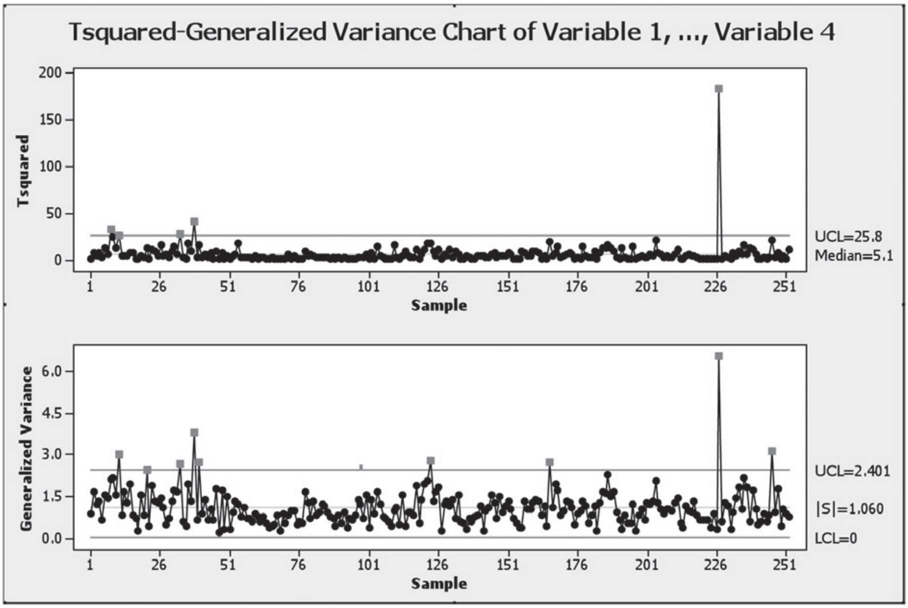
Illustrations of processes which are both multivariate and serially correlated are numerous in the production of industrial gases, silicon chips, and highly technical computer-driven products and accessories. In optical communication products manufacturing, the production of fiber optic is based on SiO_2 rods made from the 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 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.

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 ARL. In processes that have serial correlation, estimation becomes the key to correct construction of control charts. Adopting workable estimators is then an important issue.

Research on quality control charts for correlated processes focused on univariate processes. Box et al. (1994) and Berthouex et al. (1978) noticed and discussed the correlated observations in production processes. Alwan and Roberts (1988) proposed a general approach to monitor residuals of univariate auto correlated time series where the systematic patterns were filtered out and the special changes were more exposed. Other studies included 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 et al. (2002) and West and Jarrett (2004). English and Sastri (1990) and 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) provided newer methods for enabling better MPC methods.

To consider how the MPC system works data from a manufacturing process to exemplify the system was collected. Note the simplicity of interpretation in Figure 1. The control charts, each containing a different multivariate algorithm, produced results simple to interpret. There existed on either control chart only one control limit which a manager would have to interpret. The *lower control limit* (LCL) did not exist on the upper chart, and the LCL equaled zero on the lower chart. Hence, only points (observations) above the *upper control limit* (UCL) yielded a signal that the process was out of control. The supply management system manager can more easily determine the total cost per unit of the supply chain management system and the likelihood of meeting the "due time" by the methods developed by Sun et al. (2006). While the mathematics of an MPC can be more difficult for some to understand, the resulting control charts give rise to a system where a manager can meet the primary goals of the supply chain management system.

Figure 1: *Interaction between Acquisition Utility and Identity Consumption Among Men*



Note: Upper chart contains five points out of control and seventeen points almost out of control in T-Squared Chart. Lower chart (generalized variance) denotes eight points out of control and a large number nearly out of control. Only one control limit for ARL, to determine whether a is in control or not. This is a specific advantage for supply chain system managers. Last, MPC models of this type are more efficient in controlling the Probability of a Type 1 error and should have far less false signals.

Conclusions

This manuscript discussed the control chart usage and illustrated why better procedures are available to supply chain managers. For example, methods developed by Alwan and Roberts (1988) utilizing residual chart analysis were illustrated. Later, methods such as transfer function application and a traditional multivariate Hotelling T^2 chart to monitor multivariate and multivariate serially correlated processes (those with dynamic inputs) were explored. The scheme can be viewed as a generalization of Alwan and Roberts' (1988) special cause approach to multivariate cases. The guideline and procedures of the construction of VAR residual charts were also detailed in this paper. Molnau, Montgomery, and Runger (2001) produced 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 was heretofore not reported. In addition, more recent studies by Kalagonda and Kulkarni (2003) and Jarrett and Pan (2006, 2007a, 2007b) indicated 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 provided more statistically accurate and efficient methods for determining when processes are in or not in 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 provided methods for MPC charts focusing on the average run length. The purpose was 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. Further, it can be seen from Sun and Matsui (2008) that supply chain systems managers can minimize supply chain costs and in turn, have a system that is more competitive. Efficient supply chains are what both customers and suppliers need. The costs of security, stoppages, and threats to the supply chain will diminish when managers explore the usefulness of multivariate methods noted before. Lastly, these supply managers must be trained, retrained and continually trained in those methods that best fit the supply chain environment. In the future, it can be expected that examples of the efficiency of MPC in the supply chain system will occur such as with Pan and Jarrett (2013), who utilized methods of operations research on stable time series to improve the construction of control chart construction. Hence, the future is bright if these process control systems become a central part of the supply chain management system.

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Appendix 1

EWMA chart achieves 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 (Box & 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 defined by

$$Z_{i=}\ \lambda\overline{X}_i + (1-\lambda)Z_{i-1} \quad \text{with} \quad 0 \leq \lambda < 1,\ Z_o = \mu_o \qquad (1)$$

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

$$UCL = \mu_o + k\bar{\sigma}_{\bar{x}}\sqrt{\frac{\lambda}{2-\lambda}\ [1-(1-\lambda)^{2i}]} \qquad (2)$$

$$LCL = \mu_o + k\bar{\sigma}_{\bar{x}}\sqrt{\frac{\lambda}{2-\lambda}\ [1-(1-\lambda)^{2i}]} \qquad (3)$$

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

$$UCL = \mu_o + k\bar{\sigma}_{\bar{x}}\sqrt{\frac{\lambda}{2-\lambda}} \qquad (4)$$

$$LCL = \mu_o + k\bar{\sigma}_{\bar{x}}\sqrt{\frac{\lambda}{2-\lambda}} \qquad (5)$$

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 (ARL) performance.

In many situations, the sample size used for process control is n = 1; that is, the sample consists of an individual unit (Montgomery & 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 = abs (X_i – XI-1) an estimate of б is

$$б = \frac{\overline{MR}}{d_2} = \overline{MR}/1.128 = 1.128 \qquad (6)$$

Because d = 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:

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

$$CL = \bar{X}$$

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

For a control chart for moving ranges:

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

$$CL = \overline{MR}$$

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