2013

The Quality Movement in the Supply Chain Environment

Jeffrey E. Jarrett
University of Rhode Island, jejarrett@uri.edu

Citation/Publisher Attribution
Jarrett, J.E. (2013). The Quality Movement in the Supply Chain Environment. *Journal of Business & Management, 19*(2), 21-34.
Available at: https://www.chapman.edu/business/_files/journals-and-essays/jbm-editions/13-0977_JBM-vol1no2_FINAL.pdf

The Quality Movement in The Supply Chain Environment

(July 16, 2013)

Jeffrey E. Jarrett, Ph.D.
University of Rhode Island
Management Science and Finance
jejarrett@mail.uri.edu

Abstract

The purpose is to introduce the demand for the quality movement 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. The purpose is to reduce costs in the supply chain system and improve the probability of meeting the "due time."

Key Terms:
"Due Time'
Expected Total Cost per Unit in the Supply Chain System
Supply Chain System
Statistical Process Control
SPC, MPC
Multivariate Process Control
Auto correlated time series

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."

The philosophy and design of quality improvement is to achieve the best economic results of production and supply chain management. Stated differently 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 manuscript 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 notion of statistical process (or quality) control (SPC) fits and why it is so vital to the performance of supply chain environment to focus on where the notion of SPC fits and why it is so vital to the performance of supply chains in the global environment. In turn, we introduce and discuss the desire for more sophisticated methods to insure that quality and improvement is maintained in production processes involving more and greater sophisticated production method.

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 and 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.

Furthermore Sun et al. (2006 and 2008) proposed control chart systems in the supply chain management system to improve customer satisfaction of suppliers br . Their purpose was to show the mathematical foundation 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. Their study gave evidence as to the use simple univarte control on how the process of SPC can reduce shipping costs and make certain that due time for arrivals are met. Their study was limited to simple control charts and not to the important question of whether SPC systems can vary due to whether simple control chart design is the basis of the system or whether 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 another system or systems. Quality management including SPC is to positively impact the supply chain to reduce the total costs of manufacture 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. We propose in this manuscript that supply chain systems become both more efficient by reducing costs of unfit product which result in greater costs to both suppliers and customers and to meet the constraints on the system by “due times” and the loss of faith of customers who depend on supplies conforming to the goals of other methods such as “just-in-time,” optimal production scheduling and other methods to streamline manufacture 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 present and the focus I only the control of only 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 in order to see how they may be improved by more sophisticated methods having the same goal.

Univariate Control Charts

A Shewhart control chart 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 [See the Appendix for a discussion of the development of the EWMA control chart]

Although very useful, more recent studies indicate that misplaced control limits are present in many applications as discussed in the next section. These are the methodologies commonly scene in quality management programs. For example Kuei et al., (2008) indicated that quality management practices are “closely associated” with better supply chain performance and greater capabilities. Flynn and Flynn (2005) also supported by empirical evidence the desire for integration of quality management with supply chain management. In addition Kaynak and Hartly (2008) provided empirical data and analysis by statistical methods the relationships between quality management and performance measures to futher the improvement of customer relations and other constructs. Finally, Jarrett (2012) produced information suggestion 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 or quality management with supply chain management systems. Whereas EWMA charts may produce better control charts than simple Univariate control charts, you will l see in the later sections that more sophisticated control charts will 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 (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), and basic rolling operations (Xia, Rao, Shan and Shu, 1994).

Several models have been proposed to monitor processes with auto correlated 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 (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 determined by a smoothed estimate process variability. Lu and Reynolds (2001) 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 (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, et al. (1998), and Box, Jenkins, and Reinsel (1994, pp. 473-474). Atienza *et al.* 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 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 (2000, pp. 675-679).

When processes violate the assumptions of simple Univariate control charts, another method for SPC must be found [Woodall (2000)]. Earlier we learned that the placement of quality control limits (Sun and Matsui, 2006 and 2008) cause changes in the expected total cost per unit in the supply and the "due time" as well, misplacement of control by the convention simple control charts will have great effects 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 like be to make the prevailing supply chain system noncompetitive. If this is so, we should examine what other SPC systems should be utilized to make the supply chain system competitive. Last, a question remains as to whether the poalsoals of reducing cost of the supply and improvement in meeting the "due time" will be met by the Always and Roberts method/ Since , we have 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 product requiring additional effort to rework nonconforming unts, a manger can only expect reduce costs and increase the probability of meeting "due time" requirements. One additional model proposed by West, Delana and Jarrett (2002) follows a transfer function model to solve problems having dynamic behavior. The result is to design a SPC system to produce dynamic control charts having control limits that do not violate the assumption of no autocorrelation in the various time series of data. Their model is based on one and follows a by Chen and Liu (1993a,1993b). and follows the transfer function model of Box and Tiao (1975). Specific applications of the last model are given by Box, Jenkins and Reinsel (1994, p 392, or 2008) for the development of the transfer function term, and Box, Jenkins and Reinsel (1994, p 462, or 2008) for details of the intervention term. Other examples are 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, in addition, 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. However, further research into the relation of these methods 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 disturbance arise.

Multivariate Control Charts (MPC)

Charts having 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* (ARP), 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 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.

Interpretation of Multivariate Process Control Control Charts

Multivariate quality control (MPC) charts (Hotelling, 1947, Jackson, 1956, 1959 and 1985, Hawkins, 1991, and 1993, Kalagonda and Kulkarni, 2003 and 2004, Wierda, 1994, and Jarrett and Pan, 2006, 2007a and 2007b, and 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 or α).**
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 the book by 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 **SiO2** 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 auto correlated 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.

Research on quality control charts for correlated processes focused on Univariate processes. Box, Jenkins, and Reincil (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 auto correlated 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.

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

--Insert Figure 1--

Conclusions

This manuscript 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 and 2004), and Jarrett and Pan, (2006, 2007a and 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. Further we have seen from Sun and Matsui (2006, 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. Last, these supply managers much be trained, retrained and continually trained in those methods that best fit the supply chain environment. In the future, we expect that examples of the efficiency of MPC in the supply chain system will occur such as 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,.

References

Alwan, B.M., and Roberts, H.V. (1988) "Time-Series Modeling for Detecting Level Shifts of Auto correlated Processes", *Journal of Business and Economics Statistics*, 6, 87-96

Alwan, B.M., and Roberts, H.V. (1995 The Problem with Misplaced Control Limits, *Applied Statistics*, 44, 269-278

Alwan, B.M. (1992) Effects of Autocorrelation on Control Charts, *Communications in Statistics-Theory and methods*, 21, 4, 1025-1049

Alwan, L.C. (2000) *Statistical Process Analysis*, Irwin-McGraw-Hill, New York, NY

Atienza, O.O., Tang, L.C., and Ang, B.W. (1998) "A SPC Procedure for Detecting Level Shiftsof Auto correlated Processes," *Journal of Quality Technology*, 30, 340-351

Berthouex, P.M., Hunter, E. and Pallensen, L (1978), "Monitoring Sewage Treatment Plants: Some Quality Control Aspects", *Journal of Quality Technology*, 10, 4, 139-149

Box G.E.P., Jenkins, G.M. and Reinsel, G.C. (1994, and 2008) *Time Series Analysis, Forecasting and Control*, Prentice-Hall, Englewood Cliffs, NJ

Box, G.E.P. Jenkins, G.M. and Reinsel, G.C. (1994 and 2008) *Time Series Analysis: Forecasting and Control 3rd and 4th ed.*, Wiley, ISBN: 978-0-470-27284-8

Box, G.E.P. and Luceno, A. (1997) *Statistical Control: By Monitoring and Feedback Adjustment* Wiley-Interscience

Box, G.E., and Tiao, G.C. (1975) "Intervention Analysis with Applications to Economic and Environmental Problems," *Journal of the American Statistical Association*, 70, 70-79.

Chang, I, Tiao, G.C. and Chen, C. (1988) "Estimation of Time Series Parameters in the Presence of Outliers," *Technometrics*, 30, 193-204

Chen, C. and Liu, I., (1993a) "Joint Estimation of Model Parameters and Outlier Effects in Time Series," *Journal of the American Statistical Association*, 88, 284-297

Chen, C. and Liu, I., (1993b) "Forecasting Time Series with Outliers," *Journal of Forecasting*, 12, 13-35

Boyles, R.A. (2000) "Phase I Analysis for Auto correlated Processes," *Journal of Quality Technology*, 32, 395-409

Elsayed, E. A. and Zhang, H., (2007) "Design of Optimum Simple Step-Stress Accelerated Life Testing Plans," *Recent Advancement of Stochastic Operations Research*, Edited by S., Dohi, T., S. Osaki and Sawaki, K., World Scientific, Singapore, January 2007

English, J.R. and Sastri, T. (1990) “Enhanced Quality Control in Continuous Flow Processes”, *Computers and Industrial Engineering*, 19, 258-262

Flynn, B. B., and Flynn, E. J. (2005) “Synergies between supply chain management and quality management: emerging implications,” *International Journal of Production Research*, 43, 16 , 3421-3436

Harris, T.J., and Ross, W.H. (1991), “Statistical Process Control Procedures for Correlated Observations”, *Canadian Journal of Chemical Engineering,* 69, 48-57

Hawkins, D.M. (1991) “Multivariate Quality Control Based on Regression Adjusted for Variables”, *Technometrics,* 33, 1, 61-75

Hawkins, D.M. (1993) “Regression Adjustment for Variables in Multivariate Quality Control”, *Journal of Quality Technology*, 25, 3, 37-43

Hotelling, H. (1947) “Multivariate Quality Control”, *Techniques of Statistical Analysis*, Eisenhart, Hastay, and Wallis (eds.), McGraw-Hill

Hunter, J.S. (1986) “The Exponentially Weighted Moving Average,” *Journal of Quality Technology,* 18, 4, 203-210

Jackson, J.E. (1956) “Quality Control Methods for Two Related Variables”, *Industrial Quality Control*, 12, 7, 4-8

Jackson, J.E. (1959) “Quality Control Methods for Several Related Variables”, *Technometrics*, 1, 4, 359-377

Jackson, J.E. (1985) “Multivariate Quality Control”, *Communications in Statistics-Theory and Methods*, 14, 110, 2657-2688

Jarrett, J.E. and Pan, X (2006), “The Quality Control Chart for Monitoring Multivariate Auto correlated Processes, *Computational Statistics and Data Analysis*, 51 , 38621-3870

Jarrett, J.E. and Pan, X (2007a) “Using Vector Autoregressive Residuals to Monitor Multivariate Processes in the Presence of Serial Correlation,” *International Journal of Production Economics*, 106. 204-216

Jarrett, J.E. and Pan, X (2007b) “Monitoring Variability and Analyzing Multivariate Auto correlated Processes” *Journal of Applied Statistics* 34 (4) 459-469

Jarrett, J. E. (2012) “Perspectives on the quality movement in the supply chain environment,” *Problems and Perspectives in Management*, 10, 2, 98-105

Kalagonda, A.A., Kulkarni, S.R. (2003) Diagnosis of multivariate control chart signal for auto correlated processes, *Journal of Applied Statistics* 31 (3): 317-327

Kalagonda, A.A., Kulkarni, S.R. (2003) Diagnosis of multivariate control chart signal for Autocorrelated processes. *Journal of Applied Statistics* 31 (3): 317-327

Kaynak, H., and Hartly, J. (2008) A replication and extension quality management into the supply chain," *Journal of Operations Management*, 26, 4, 468-489

Kim and May, (1994) An optimal neural network process model for plasma etching. *IEEE Transactions on Semiconductor Manufacturing*. v7 i1. 160-175

Koksalan, M. Erkip, N. Moskowitz H. (1999) "Explaining beer demand: A residual modeling regression approach using statistical process control" *Int. J. Production Economics* 58 265-276.

Kuei, C., Madua, C., Lin, C. (2008) "Implementing Supply Chain Quality Management," *Total Quality Management*, 19, 11, 1127- 1140

Lee, H.L. and Whang, S (2003) Higher Supply Chain Security with Lower Cost: Lessons from Total Quality Management, Research Paper No. 1824, Stanford Graduate School of Business, Palo Alto, CA

Lowry, C.A.W. Woodall, C.W. Champ and Rigdon, S.E. (1992) "A Multivariate Exponentially Weighted Moving Average Control Chart", *Technometrics*, vol. 43, 46-53

Lowry, C.A. and Montgomery, D.C. (1995) "A Review of Multivariate Charts, *IIE Transactions*, 27, 800-810

Lu, C.W., and M.R. Reynolds (1999) "Control Charts for Monitoring the Mean and Variance of Auto correlated Processes", *Journal of Quality Technology* 31, 259-274

Maragah, H.O., and Woodall, W.H. (1992). "The Effect of Autocorrelation on the Retrospective X-Chart", *Journal of Statistical Computation and Simulation*, 40, 1, 29-42

Mastrangelo, C.M. and Forrest, D.R. (2002) "Multivariate Auto correlated Processes: Data and Shift Generation", *Journal of Quality Technology*, 34, 2, 216-220

Mestek, O. Pavlik. J. and Suchanek, M. (1994) "Multivariate Control Charts: Control Charts for Calibration Curves". *Fresenius Journal of Analytical Chemistry* 350, pp. 344-351

Molnau, W.E., Montgomery, D.C., and Runger, G.C. (2001) "Statistically Constrained Economic Design of the Multivariate Exponentially Weighted Moving Average Control Chart", *Quality and Reliability Engineering International*, 17, 1, 39-49

Montgomery, D.C. and C.M. Mastrangelo (1991) "Statistical Process Control in a Computer-Integrated Manufacturing Environment", *Statistical Process Control in Automated Manufacturing*, edited by J.B. Kates and N.F. Hunele, Marcel Dekker, Inc. Series in Quality and Reliability, New York

Montgomery, D.C. (2005) *Introduction to Statistical Quality Control* fifth ed., Wiley

Montgomery, D. C. and Friedman, J.J. (1989) "Statistical Process Control in a Computer-Integrated Manufacturing Environment," *Statistical Process Control* in *Automated Manufacturing*, edited by J.B. Kates and N.F. Hunele, Marcel Dekker, Inc. Series in Quality and Reliability, New York

Montgomery, D.C. and Runger, G. C. (2003) *Applied Statistics and Probability for Engineers*, 3rd ed., Wiley, New York

Montgomery, D.C. and Wadsworth, H.M. (1972) *"Some Techniques for Multivariate Quality Control Applications," ASQC Technical Conference Transactions,* Washington, D.C., May, 427-435

Pan, X. and Jarrett, J. (2004) "Applying State Space into SPC: Monitoring Multivariate Time Series", *Journal of Applied Statistics*, 31, 4, 397-418

Smith, A.E. (1993) Predicting Product Quality with Back propagation: A Thermoplastic Injection Molding: Case Study, *International Journal of Advanced Manufacturing Technology*, 8, 252-257

Sullivan, J.H. and Woodall, W.H. (1996) A Review of Multivariate Charts, *Journal of Quality Technology,* 28, 4, 261-264

Sun, J., Tsubaki, M and Matsui, M. (2006) Economic models of the mean chart with tardiness penalty in finite due time processes, in: *Journal of Japanese Industrial Management Association*, (in Japanese) 57, 5, 374-387

Sun, J. and Matsui, M. (2008) "A control chart design used in supply chain management system," *International Journal of Management Science and Engineering Management*, 3, 3, 211-219

Testik, M.C. (2005) "Model Inadequacy and Residuals Control Charts for Autocorrelated Processes, *Quality and Reliability Engineering,* 21, 115-130

Tracy, N.D., Young, J.C. and Mason, R.I. (1992) "Multivariate Quality Control Charts for Individual Observations" *Journal of Quality Technology*, 24, 2, 88-95

Wardell, D.G., Moskowitz, H. and R.D. Plante (1994) "Run-Length Distribution of Special-Cause Control Charts for Correlated Processes", *Technometrics, 36*

West, D., Delana, S. and Jarrett, J (2002) “Transfer Function Modeling of Processes with Dynamic Inputs”, *Journal of Quality Technology* 34, 3, 315-321

West, D., and Jarrett, J. (2004) “The Impact of First Order Positive Auto regression on Process Control”, *International Journal of Business & Economics,* 3, 1, 29-37

Wierda, S.J. (1994) “Multivariate Statistical Process Control: Recent Results and Directions for Future Researches:, *Statistica Neerlandica,* 48, 147-168

Wright, C. M., Booth, D. E. and Hu, M. Y. (2001) “Joint Estimation: SPC Method for Short-run Autocorrelated Data,” *Journal of Quality Technology*, 33, 3, 365-368

Woodall, W.H. (2000) Controversies and Contradictions in Statistical Process Control, *Journal of Quality Technology*, 32, 4, 341-350

Xia, Q., Rao, M., Shan, X., and Shu, H. (1994). Adaptive Control of a Paperboard Machine, *Pulp and Paper Canada*, 95:51-55

Yang, S.F. and Rahim, R.A. (2005) “Economic Statistical Process Control for Multivariate Quality Characteristics under Weibull shock model”, *International Journal of Production Economics*, 98, 215-226

Yeh, A.B., Hwang, L., Wu, Y. (2004) “A Likelihood-Ration-Based EWMA chart for monitoring variability of multivariate normal processes”, *IIE Transactions, 36, 865-879*

Zhang, C., Yu, H. and Huang, X. (2009) “Quality Control Strategy in Supply Chain under symmetric information,” *International Journal of Operations Research*, 4, 1, 97-116

Appendix

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 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

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

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 $CL = \mu_o$ 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 get 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 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 = abs (X_i – X_{i-1}) an estimate of **б** is

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

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

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

$$CL = \bar{X}$$

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

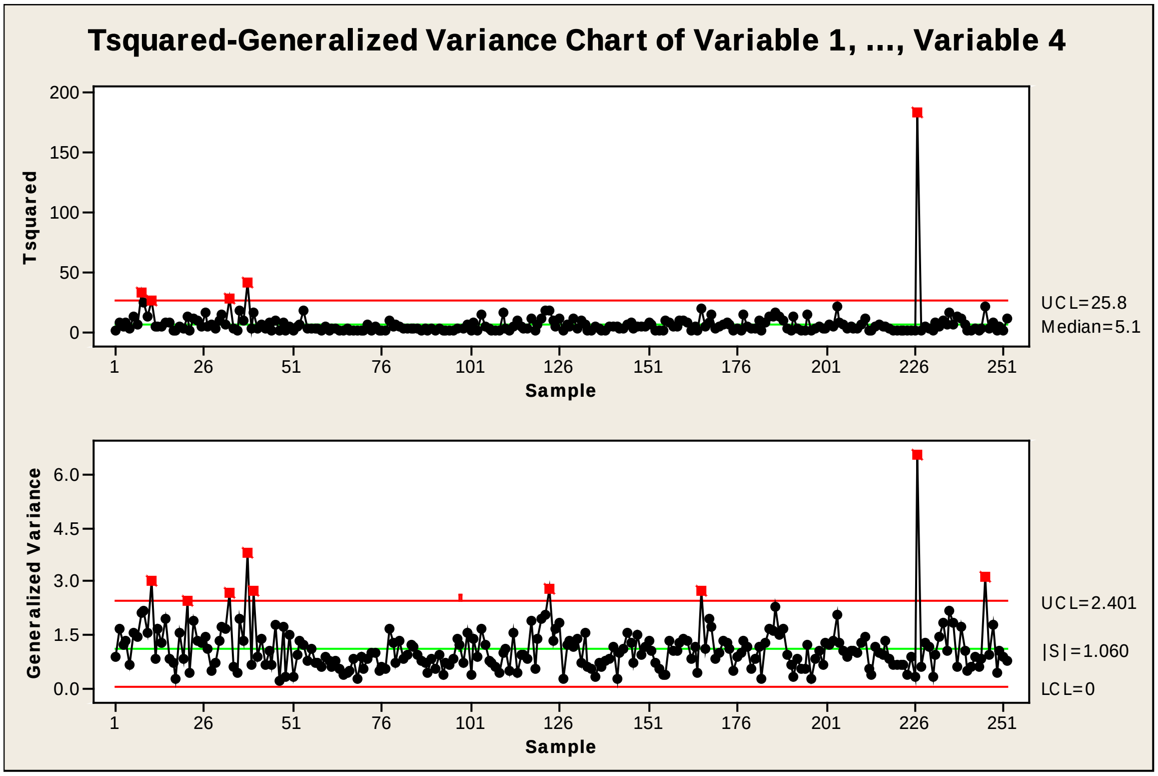
For a control chart for moving ranges

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

$$CL = \overline{MR}$$

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

Figure 1



Result of MPC Using *Minitab*® Quality Software

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.

BIO

Jeffrey E. Jarrett is former Chairperson of the Department of Management Science and Professor of Management Science and Finance at the University of Rhode Island. He holds degrees from the University of Michigan and New York University where he studied with W. Edwards Deming, among others. He has published extensively in The Accounting Review, Decision Sciences, Journal of Business Finance and Accounting, Journal of Accounting Research, Journal of Finance, Management Science, OMEGA:The International Journal of Management Science, Journal of Business Forecasting, Statistical Software Newsletter, Journal of Business and Economic Statistics, Journal of the American Statistical Association, Atlantic Economic Journal, Review of Business and Economic Research , Statistics and Computing, Midwestern Journal of Business and Economics, Financial Engineering and Japanese Markets, Economic and Financial Modelling, International Journal of Business and Economics, and the International Journal of Forecasting Journal of Applied Statistics, International Journal of Empirical Research, International Journal of Business and Economics, Computational Statistics and Data Analysis, Cummunications in Statistics, International Journal of Economics and Management Engineering and Applied Economics among others. Further , he presented many research and summary papers at international and national conferences.