A Review and Literature Survey of Control Charts Using New Classification Schemes
- 새로운 분류체계를 이용한 관리도의 문헌고찰과 검토 -

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요 지

본 논문은 새로운 3차원 분류체계를 이용해서 관리도의 문헌을 고찰하고 검토하는데 연구 목적이 있다. 1차원 분류체계는 시간에 따른 연속된 관측치의 관계가 독립인가 자동상관인가로 나누어지며 2차원 분류체계는 독립관측치인경우 가중치 방법에 따라 Shewart, MA, EWMA, CUSUM Charts로 분류되며 자동상관된 관측치인 경우 모델링 방법에 따라 ARIMA, Spectral Charts로 분류된다. 3차원 분류체계는 품질특성인 변수의 수와 종속관계에 따라 일변량과 다변량으로 나누어 진다. 재래식 생산, 자동화 생산, 혹은 장치산업에 적용될 수 있는 관리도가 이 분류체계에 따라 장으로 구분되어 고찰된다. 이는 실무진들의 이해를 돕기위한 지침으로 활용될 수 있다.

1. Introduction

This paper is a review and literature survey regarding the risk design of control charts. This paper is restricted to risk-based charts for product and process control and does not include economic design of control charts and acceptance control charts.

Gibra(1975) reviewed developments in control chart techniques for the three decades immediately preceding 1975. For convenience of presentation, the following classifications of control chart techniques were used:

(a) Shewart Control Charts and Their Ramifications
(b) Modifications of Shewart Control Charts
(c) Cumulative Sum Control Charts
(d) Economic Design of $\overline{x}$-Control Chatrs
(e) Acceptance Control Charts
(f) Multi-Characteristic Control Charts

Vance(1983) presented a bibliography of statistical quality control chart techniques for the years 1970 to 1980. The following classifications were used:

(a) Shewart Control Charts and Their Modifications
(b) Cumulative Sum Control Charts and Related Developments
(c) Economic Design of Control Charts
(d) Acceptance Control Charts
(e) Multi-Characteristic or Multivariate Control Charts

Several reviews of literature concerning the economic design of control charts have been conducted by Montogomery(1980), V.Collani(1988), and Svoboda(1991).

In comparision with the above reviews, this paper is to propose three dimensions for classifying control charts, and to review the recent developments and future directions in this area. And this paper is to study with the aim of developing guidelines for practitioners.

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The rest of the paper is organized into five sections. In the following section a classification scheme is given. Section 3 contains a review of control charts for independent observations in conventional manufacturing. Section 4 reviews control charts for autocorrelated observations in automated manufacturing and process industry. Section 5 suggests three directions for future research in advanced automated manufacturing and process industry. Finally, some concluding remarks are given in Section 6.

2. Classification of Control Charts

Numerous schemes have been proposed for categorizing control charts. For our purposes we desire a broad classification which allows us to emcompass the general characteristics of both theory and practice. With this in mind, we propose the following three dimensions for classifying control charts:

(a) The relation of successive observations over time
(b) The method of weighting and modelling
(c) The number and relation of variables

The first dimension is a key distinction. This is classified by the property that successive observations are independent or dependent over time. This distinction is made in terms of an independent observations versus autocorrelated observations. Control charts for independent observations can be applied to conventional manufacturing. Control charts for autocorrelated observations can be applied to automated manufacturing and process industry.

The second dimension indicates the method of weighting and modelling. For independent observations one key to understanding the differences between the Shewart, Moving average(MA), Cumulative Sum(CUSUM), Exponentially Weighted Moving Average(EWMA) control charts rests in knowing how each charting technique uses the data generated by the production process. The data weighting functions for the Shewart, MA, CUSUM, and EWMA control charts are displayed in Figure 1 (Hunter[1986]).

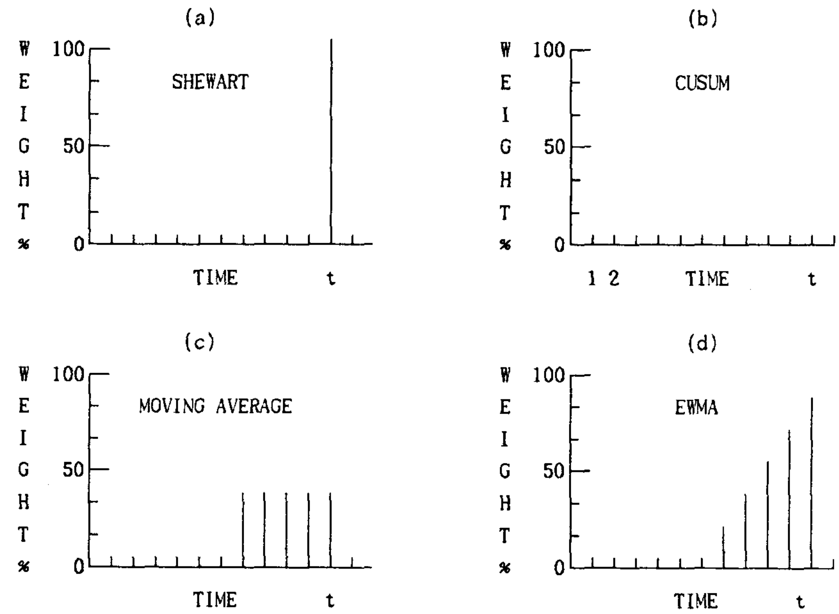

FIGURE 1. Data Weighting for the Shewart, CUSUM, Moving Average and EWMA Charts.

In the presence of data correlation the process can be described by autoregressive integrated moving average(ARIMA) models (time-domain models). This approach leads to two basic charts rather than one:

(a) Common cause chart (CCC) : a chart of fitted values based on ARIMA models.

This chart provides guidance in seeking better understanding of the process and in achieving real-time process control.

(b) Special cause chart (SCC): a chart of residuals (or one-step prediction errors) from fitted ARIMA models.

This chart can be used in traditional ways (e.g., Shewart, MA, CUSUM, and EWMA control charts for independent observations) to detect any special causes, without the danger of confounding of special causes with common causes. The independent observations model guides the interpretation of this second chart: all traditional tools of process control are applicable to it (Alwan et al. [1988]).

Spectral models (frequency-domain models) are used to detect and evaluate periodicities in equally spaced time-ordered data. This control chart detects cycles in the process mean (Beneke at al. [1988]). And we can consider the effect of data correlation on traditional control charts.

The third dimension is concerned with the number and relation of variables describing the quality characteristics. Many problems, in automated manufacturing and process industry, involve a vector of measurement of several (multivariate) characteristics rather than a single (univariate) characteristic in conventional manufacturing. Although one could monitor the process using separate charts of the variates, to the extent that these measurements are mutually correlated, one will obtain better sensitivity using multivariate methods that exploit the correlations (Hawkins [1991]).

3. Review of Control Charts for Independent Observations

In conventional manufacturing, a state of statistical control is identified with a process generating independent and identically distributed random variables (IID). We review four traditional control charts.

3.1. Shewart Charts

In a Shewart control chart upper and lower control limits for the plotted points are established around the process mean μ at points $\mu \pm 3\sigma$, the "three-sigma" limits where σ is the standard error of the points plotted. In a process under ideal control the mean μ will equal a fixed target value μ_0 required by the process specifications. A signal that the observed process requirements attention is given whenever the most recent plotted point falls outside the control limits. In practice, the Shewart control chart is established empirically. Usually, repeated random homogeneous samples of four or five observations each are gathered from the process, and, based upon the sample averages $\bar{x}$ and ranges R (or estimates S of the standard deviation), empirical control charts are established with the center line of the chart the grand average $\bar{\bar{x}}$. The standard Shewart chart with its $\pm 3\sigma$ limits only rarely provides a signal when the current process is at its mean level, thus keeping the type I error, or "α risk," small (Hunter [1986]).

3.1.1. Univariate Shewart Charts

Larson (1969) presented the computer program for plotting $\bar{x}$-and R-charts and Nelson (1984,1985) recommended eight charts for special causes applied to Shewart control charts. Nelson considered the group control chart in 1986 and formulas for standardizing four types of Shewart control charts in 1989. The extent to which the cumulative sum chart and other devices are competitors to $\bar{x}$-and R-chart was discussed by Craig (1969).

Scoring scheme for a run sum test was provided by Reynolds (1971) and average run lengths (ARLs) of the zone control chart were presented by Davis et al. (1990).

Weindling et al. (1970) showed that the Shewart control chart for means can be made sensitive to small changes by adding a pair of warning limits, located inside the action limits, and taking action when a run of a specified number of consecutive means falls between the warning and action lines. The effect of non-normality investigated five populations on the control limits of $\bar{x}$ chart was examined by Schilling et al. (1976).

For the sensitivity of a chart to a process mean, Wheeler (1983) gave tables of the power function for $\bar{x}$ charts and Palm (1990) provided the practitioner with tables of run length percentiles. The effect of measurement error on the power of a control chart was examined for the case where both the process average and variance can change (Kanazuka [1986]).

Langenberg et al. (1986) introduced a modified approach to the computation of control limits for $\bar{x}$-and R-charts. This procedure consists of replacing $\bar{x}$ with the trimmed mean of the subgroup averages, and R with the trimmed mean of the subgroup ranges. Rocke (1989) proposed six robust control-charting procedures. The first method (mean/range) is the standard $\bar{x}$ and R chart with control limits determined from the mean of subgroup means and the mean of the subgroup ranges. The second type of chart (trimmed/range) consists of $\bar{x}$ and R charts with the 25% trimmed mean of the subgroup means and the 25% trimmed mean of the subgroup ranges used to produce the limits. The third type (median/range) similarly uses the median to summarize the subgroup statistics. The fourth type (mean/IQR) is the mean of the subgroup means and IQR's to set limits, and the fifth (trimmed/IQR) uses the 25% trimmed mean of the means. The final chart (median chart) consists of median and IQR charts with the mean of the subgroup medians and the mean of the subgroup IQR's used to set limits.

Recent theoretical studies have shown that, for all but very large process shifts, control charts using variable sampling interval (VSI) schemes are more efficient in their detection of shifting processes than the more conventional fixed sampling interval (FSI) schemes (Burr [1969], Reynolds et al. [1988], Nelson [1988,1990], Runger et al. [1991], Amin et al. [1993]). A common rule of thumb is that conventional control limits for Shewart control charts, no standards given, should be based on at least 25 subgroups. But Hillier (1969) and Yang et al. (1970) presented information for evaluating the lack of reliability of these control limits when they are based on a small number of subgroups.

Mandel (1969) and Quesenberry (1990) combined the conventional control chart and regression analysis. Cyclic data control charts by Johnson at al. (1979) consisted of controlling subgorup averages by using the standard deviation of the subgroup average. Ciminera et al. (1989) suggested control chart to monitor automated instruments used in the routine daily assay of body fluid samples from a chemical laboratory.

Statistical process control (SPC) is much more than statistics to control output by adjusting the process. SPC is called CITS - Continuous Improvement Through Statistics. Mortimer (1988) and Drozda (1989) presented some successful applications in manufacturing experience.

3.1.2. Multivariate Shewart Charts

Jackson et al. (1957) used Hotelling's T^2 as the appropriate statistic for multivariate control chart and applied three area of Hotelling's developments, that of total variation, principal components and residual sum of squares. Phillips (1987) and Johnson et al. (1992) explained Hotelling's T^2 in detail.

Jackson (1985) presented the T^2 chart, the use of principal components, multivariate analogs of

CUSUM charts, the use of the Andrew's procedure, and multivariate acceptance sampling.

Principal component analysis is a method of transforming a given set of variables into a new set of composite variables. These new varialbes are orthogonal to each other and account for the variance in the original data. It may be found that fewer principal components that the number of original variables are needed to account for the total variance. It is for these reasons that principal components are often used in exploratory data analysis and data reduction. Hawkins (1974,1982) and Raveh (1985) discussed the use of principal components in data analysis. Jackson (1957,1979,1980,1981a,b,1985) explained the use of principal components in quality control in conjunction with the T^2 control chart. Schall et al. (1987) developed a method of using principal components to control a process which has many output characteristics affecting the quality of the final product. The disadvantage to using principal components and the T^2 statistic is that both statistics may not have any physical meaning.

Srivastava et al. (1985) and Daganaksoy et al. (1991) suggested the diagnostic scheme to detect outliers in a multivariate manufacturing environment.

Graphical procedures for multivariate quality control were proposed by Kulkarni et al. (1984, 1986), Blazek et al. (1987), and White et al. (1987).

Saboo et al. (1987) decribed certain correlation process in flowlines and Wesolowsky (1990) dealed with acceptance control charts in which two processes can be positively or negatively correlated.

3.2. MA Charts

The desire to employ historical data more resourcefully has occasionally led to the use of the moving average. A plot of moving average of k=5 observations simply displays the average of the five most recent observations. Each new entering observation forces the oldest in the group out of the computation. The moving average smooths a time series. The moving average can produce cyclic and trend-like plots even when the original data are themselves independent random events with a fixed mean. This characteristic lessens its usefulness as a control mechanism (Hunter [1986]).

3.2.1. Univariate MA Charts

Control charts for individual measurements in combination with a moving range based in two consecutive measurements were presented by Nelson (1982,1987) and Crowder (1987a,b).

Moving averages were discussed by Nelson (1983) and Montogomery (1985)

3.2.2. Multivariate MA Charts

Choi (1992a) applied multivariate MA statistic to the white residuals from the multivariate AR(2) model.

3.3. EWMA Charts

The EWMA (GMA : geometric moving average) is a statistic with the characteristic that it gives less and less weight to data as they get older and older. A plotted point on an EWMA chart can be given a long memory, thus providing a chart similar to the ordinary CUSUM chart, or it can be given a short memory and provide a chart analogous to a Shewart chart. The EWMA is very easily plotted and may be graphed simultaneously with the data appearing on a Shewart chart. The EWMA is best plotted one time position ahead of the most recent observatrion. The EWMA equals the present predicted value plus λ times the present observed error of prediction.

Thus

$$\begin{aligned} EWMA = Z_t &= Z_{t-1} + e_t \\ &= Z_{t-1} + \lambda (X_t - Z_{t-1}) \\ &= \lambda X_t + (1 - \lambda) Z_{t-1} \end{aligned}$$

where

Z_t = predicted value at time t+1 (the new EWMA)

X_t = observed value at times t

Z_{t-1} = predicted value at times t (the old EWMA)

$e_t = X_t - Z_{t-1}$ = observed error at time t

and λ is a constant ($0<\lambda<1$) that determines the depth of memory of the EWMA (Hunter[1986]).

3.3.1. Univariate EWMA Charts

The use of EWMA fot constructing control charts for the mean of a process have been introduced by several authors. Wortham et al. (1973) presented a computer program for plotting EWMA control charts and Hunter (1986) found that the EWMA chart is easy to plot, easy to interpret, and its control limits are easy to obtain, and the EWMA leads naturally to an empirical dynamic control equation. Both ARLs and standard deviations of run lengths (SDRLs) were presented by Crowder (1987c). Crowder presented a computer program that calculated ARLs of EWMA charts in 1978d and recommended a design strategy using optimal λ plots in 1989.

Lucas et al. (1990) described the properties of EWMA control schemes and have compared them with CUSUM control schemes. The results showed that the properties of EWMA's are very close to those of CUSUM schemes. Both schemes include the one-parameter Shewart control scheme as a special case. The two parameters in the EWMA and CUSUM control schemes are used to average observations over time. This makes them less sensitive to outliers and enables them to detect small shifts more quickly than the standard Shewart control scheme. Several enhancements of EWMA control schemes were evaluated. These include a fast initial response (FIR) feature that makes the scheme more sensitive at start-up, a combined Shewart - EWMA that provides protection against both large and small shifts in the process, and a robust EWMA that provides extra protection against outliers. These enhancements work as well for EWMA control schemes as they do for CUSUM control schemes. Saccucci et al. (1990) gave a computer program for the computation of ARLs for EWMA and combined Shewart-EWMA control schemes.

For detecting increases in process variability (e.g., process standard deviation), which can have a major impact on product quality, Crowder et al. (1992) proposed using EWMA based on the log transformation on the sample variance and Hamilton et al. (1992) presented a computer program that generates a table of ARL's for a one-side EWMA control chart on a process standard deviation.

A consistent and systematic approach for deriving control charts of the EWMA to monitor the process mean and dispersion was presented by Ng et al. (1989). EWMA quality-monitoring schemes capable of detecting changes in both location and spread, referred to as omnibus (coupled) EWMA's were proposed by Sweet (1986,1988) and Domangue et al. (1991). The performance of the omnibus EWMA (n=1) schems was compared with EWMA (n=1), omnibus CUSUM (n=1), CUSUM (n=1), $\bar{x}$ chart, $\bar{x}$-warning, individuals moving range, and $\bar{x}$-R chart (Domangue et al. [1991]). The omnibus EWMA and CUSUM schemes are comparatively easy to implement. Although efficiency capable of detecting changes in both location and spread is existed in omnibus approach, some effectiveness in performance would be sacrificed more than individual apporach.

3.3.2. Multivariate EWMA Charts

Lowry et al. (1992) presented that on the basis of ARL performance the proposed procedure can perform better than the multivariate CUSUM proceduces of Crosier (1988) and Runger et al. (1991) when the process is initially out-of-control and it performs roughly the same if the shift in the mean vector is delayed. Inertial problems can delay reaction to a shift when using multivariate CUSUM or proposed charts (MEWMA charts), so Hotelling' χ^2 limits should always be used in conjunction with these charts to help to prevent such delays.

Lowry et al. (1992) regarded multivariate EWMA as a smoothing problem but Choi et al. (1992b) applied multivariate statistic to the one-step-ahead forecasted value from the multivariate IMA(1,1) model for the minimun mean-squared-error control. They presented two examples when θ's (= I-λ) in identified multivariate IMA(1,1) are both a diagonal matrix and a full matrix.

3.4. CUSUM Charts

An alternative method for plotting sequentially recorded observations x_t is to plot their cumulative sum, $\sum_{t=1}^{T} x_t$, against time t. Or, rather than the cumulative sum of the observations, one can use the cumulative sum of the deviations.

$$d_t = x_t - k$$

Where k is some convenient constant, usually the target value μ_0. Thus a CUSUM chart is the quantity

$$S_T = \sum_{t=1}^{T} (x_t - k) = \sum_{t=1}^{T} d_t$$

plotted against T. If the mean μ of the observed values x_t equals the target value, μ_0, then $S_T = \sum_{t=1}^{T} d_t$ will plot as a random walk; that is, S_T will wander randomly about zero. However, should the mean of the process differ by a slight amount δ from the target value, then the expected value of S_T will add δ with each observation. The plot of S_T thus increases or decreases depending on the sign of δ. Therefore, when plotting a CUSUM chart the analyst watches for a change in the slope of the plot of S_T as an indication of a shift in mean away from target (Hunter [1986]).

3.4.1. Univariate CUSUM Charts

Dusek et al. (1970) presented a computer program for plotting CUSUM charts and Lucas (1976) discussed v-mask control schemes provided significantly better performance than Shewart control charts for detecting small shifts of the mean from goal conditions. Several methods of designing CUSUM quality control charts were reviewed by Woodall (1986) and a computer program to calculate the ARLs of CUSUM control charts for controlling normal means was presented by Vance (1986). Kang et al. (1992) presented tables determining the decision limit of CUSUM chart by using regression recursive residuals.

Brook et al. (1972) presented a Markov chain approach to the discrete and continuous probability distribution of CUSUM length. Examples are given for the case of a Poisson random variable and a normal random variable. Woodall (1983) used a Markov process appraoch for continuous random variables involving normally distributed random variables and Woodall (1984) used a Markov chain approach for integer-valued random variables. Vardeman et al. (1985) provided some tables of ARLs for the exponential case and comment on an application of exponential CUSUM charts to controlling the intensity of a Poisson process. Yashchin (1992) discussed a nonparametric approach by using empirical distributions. Lucas et al. (1982a) and Crosier (1986) proposed schemes with

FIR features for a controlling a process mean and a Markov chain approximation is used to calculate the ARLs of the new scheme.

Lucas et al. (1982b) studied a robustness for CUSUM quality control schemes by evaluating a standard CUSUM control scheme and four modified CUSUM control schemes (i.e., Shewart-CUSUM, ignore suspected outliers, two-in-a-row rule, Winsorize outliers). Hockman et al. (1987) discussed the design and use of subvessel control in the chemical industry and two types of weighted control schemes that generalizes the basic CUSUM technique was introduced by Yashchin (1989). Reynolds et al. (1990) proposed VSI CUSUM scheme that varies the time intervals between samples depending on the value of the CUSUM control statistic.

Hawkins (1981) presented a technique for employing the same CUSUM procedure used for the mean for controlling the variance. Hawkins (1992) proposed a fast accurate approximating for ARLs to evaluate the out-of-control ARLs of location and scale CUSUM charts.

Lucas (1982b) proposed combined Shewart-CUSUM quality control schemes. In this scheme the CUSUM feature will quickly detect small shifts from the goal while the addition of Shewart limits increases the speed of detecting large shifts. Ncube et al. (1990) developed combined Shewart-CUSUM score (CUSCORE) quality control procedures. Xiao (1992) proposed a cumulative score to detect a shift in the process mean. The scheme proposed can be easily implemented and combined with the $\bar{x}$-chart. Three new control chart procedures (i.e., a new one-sided EWMA chart, a new two-side EWMA charts, the combined EWMA-CUSUM chart) were presented by Champ et al. (1991).

Yashchin (1987) and Guo et al. (1992) used CUSUM charts in industrial quality control as a means of monitoring the quality of manufactured products. Wasserman et al. (1989) considered a modified Beattie procedure for process monitoring that does not require 100% inspection and Lucas (1985, 1989) and Schneider et al. (1987) presented a scheme for CUSUM's for attributes.

3.4.2. Multivariate CUSUM Charts

Woodall et al. (1985) proposed the multiple univariate CUSUM scheme and Alwan (1986) proposed a CUSUM of the T^2 on the basis of sequential probability ratio tests. Healy (1987) pointed out that the CUSUM of T^2 may be motivated by the desire to locate shifts in variance rather than shifts in mean. Crosier (1988) suggested a CUSUM of T and multivariate CUSUM schemes. A method for obtaining multivariate control procedures based on a loss function was studied by Mohebbi et al. (1989).

Pignatiello et al. (1990) considered several distinct approaches for controlling the mean of a multivariate normal process including two new and distinct multivariate CUSUM charts, several multiple univariate CUSUM charts, and Shewart χ^2 control charts. Hawkins (1991) proposed individual combined Shewart-CUSUM charts of location and scale based on the vector of Z of scaled residuals from the regression of each variable on all others. To show the relative performance of the group CUSUM control charts, he compared the five charts (i.e., COT, CCU, MCX, MCZ, ZNO).

4. Review of Control Charts for Autocorrelated Observations

In automated manufacturing and process industry, sensors are often used for real-time, on-line data capture. In such processes, observations may exhibit serial correlation. We review two-type time series control charts and the effect of data correlation on traditional control charts.

4.1. ARIMA Charts

Mothods for dealing with autocorrelated data in the statistical process control environment have been suggested by several authors. While the tactical approaches to the problem of autocorrelation taken by authors often differ somewhat, the strategic thrust of their efforts are identical: fit an appropriate time series model to the observations and then apply control charts to the stream of residuals from this model. The typical time series model employed is the ARIMA model

$$\phi_p(B)\nabla^d x_t = \theta_q(B)a_t$$

where $\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p)$ is an autoregressive polynomial of order p, $\theta_q(B) = (1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q)$ is a moving average polynomial of order q, ∇ is the backward difference operator, B is the backshift operator, and at a_t is a sequence of normally and independently distributed random "shock" with mean zero and constant variance σ_p^2 (Montogomery et al. [1991])

4.1.1. Univariate ARIMA Charts

Automatic process control (APC) and traditional statistical process control (SPC : arguably a misnomer for statistical process monitoring) have developed in relative isolation from one another. A comparision of SPC and APC reveals the different orientations of the fields in three significant areas:

(a) Philosophy : Both fields seek to reduce deviations of some characteristic from a target value. In SPC, however, this is accomplished by monitoring a process so as to detect and remove root causes of variablity (i.e., hypothesis testing). On the other hand, APC seeks to counteract the effects of root causes through continual process adjustment (i.e., estimation).

(b) Application Context : SPC are ordinarily appropriate when it is reasonable to expect successive measurements to be well modelled as iid and one is concerned with detecting departures from such an ideal. By contrast, APC is ineffective on (even harmful to) an iid process. It is most effective in the context of a continually wandering process - for example, a process that could be well modelled by an ARMA time series.

(c) Traditional Development : APC is most often used tactically. For example, feedback controllers are typically commissioned to maintain the setpoints of important process parameters. SPC, however, is often allowed a strategic role. Control charts are kept on important quality characteristics, allowing SPC to have a direct impact on the quality of the process output (Vander Weil et al. [1992]).

Several authors by Box et al. (1976,1992), Alwan et al. (1988) MacGregor (1988), Keats et al. (1989,1991), English et al. (1990), and Vander Weil et al. (1992) discussed how to combine SPC and APC for total system improvement. Among them, Alwan et al. (1988) proposed an appealing two-step apprach as follows:

(a) A time series plot of the fitted values, without computation of control limits. This plot can be regarded as a series of point estimates of the conditional mean of a process - our best current guess based on past data of the location of the underlying process. This is a common cause chart (CCC).

(b) Standard control charts (Shewart, MA, EWMA CUSUM) for the residuals. Control limits are based on the time series model itself; for example, limits for prediction errors would be based on the standard errors of one-step-ahead forecasts. This is a special cause chart (SCC).

Berthouex et al. (1978) and Montogomery et al. (1991) developed special cause charts for the residuals from the ARIMA models. Wardell et al. (1992) compared the performance of the Shewart chart and the EWMA chart to the performance of the special cause chart and the common cause chart.

Various control chart techniques using a recursive Kalman filter were proposed by Phadke (1982), Hubele et al. (1990), and English et al. (1991)

MacGregor et al. (1993) proposed exponentially weighted moving variance and exponentially weight mean squared deviation for monitoring various types of continuous process variation when the observations are autocorrelated. Economic-process-control models in production were discussed by Drezner et al. (1989), Adams et al. (1989), Ferrell et al. (1990), and Crowder (1992).

4.1.2. Multivariate ARIMA Charts

Choi (1992a) proposed a eight special cause charts for the multivariate AR(2) model in CIMS. Choi et al. (1992b) studied a common cause chart for multivariate IMA(1,1) model in the process industry.

4.2. Spectral Charts

The time series approach presented in earlier section, which uses functions such as autocorrelation and partial autocorrelations to study the evolution of a time series through parametric models, is known as time domain analysis. An alternative approach, which tries to describe the fluctuation of time series in terms of sinusoidal behavior at various frequencies, is known as frequency domain analysis. The time domain approach and the frequency domain approach are theoretically equivalent. The reason to consider both approaches is that there are some occasions when one approach is preferable to the other for presentation or interpretation (Wei [1990]).

4.2.1. Univariate Spectral Charts

The spectral control charts based on the periodogram were studied by Beneke et al. (1988) and Spurrier et al. (1990). Brigham (1988) introduced the fast fourier transformation and its applications which are fundamental for the spectral charts.

4.2.2. Multivariate Spectral Charts

No research have been performed in this area but Priestley (1981) introduced the basic concepts of multivariate spectral analysis which are fundamental for the multivariate spectral charts.

4.3. The Effect of Data Correlation on Traditional Control Charts

Quality control chart interpretation is usually based on the assumption that successive observations are independent over time. In this section we show the effect of autocorrelation on traditional control charts.

Cryer et al. (1990) and Maragah et al. (1992) studied the effect of autocorrelation on the control charts for individual measurements in combination with a moving range. Vasilopoulos et al. (1978) and Neuhardt (1987) considered the effects of data correlation on the $\bar{x}$ chart. The performance of CUSUM control schemes for serially correlated observations were studied by Johnson et al. (1974), Harris et al. (1991), and Yashchin (1993).

5. Future Directions

In advanced automated manufacturing and process industry, the processes are much more complex. Three areas for future research which can be used effectively and powerfully in these complex processes are suggested below.

5.1. Outlier Detection Methods in Time Series

Several approaches suggested for handling outliers in time series are as follows:

(a) Methods based on Intervention Analysis
(b) Methods based on Regression Diagnostics
(c) Methods based on Missing Observations and Robust Estimation
(d) Methods based on Bayesian Analysis

Outlier methods based on intervention analysis were introduced by Fox (1972), Box et al. (1975), Bagshaw et al. (1977), Hsu (1977), Guttman et al. (1978), Pierce (1979), Bell (1984), Tsay (1984,1986,1987,1988), Ansley et al. (1985), Muirhead (1986), Harvey et al. (1984,1992), Chang et al. (1988), Deutsch et al. (1990), and Lee et al. (1992).

Outlier methods based on regression diagnostics were studied by Chernick et al. (1982), Martin et al. (1986), Khattree et al. (1987), Kohn et al. (1989), Bruce et al. (1989), Abraham et al. (1989), Bhandary (1989), and Lee (1990).

Outlier methods based on missing observations and robust estimation were considered by Jones (1980) Abraham (1981), Dunsmuir et al. (1981), Harvey et al. (1984), Ryu (1991), Delvin et al. (1975), Denby et al. (1979), Butos et al. (1986), Li (1988), and Cho et al. (1992).

Outlier methods based on Bayesian analysis were proposed by Box et al. (1968), Abraham et al. (1979), Menzefricke (1981), Spiegelhalter et al. (1982), and Ryu et al. (1989).

Embrechts et al. (1986) recommended that Andrew's plots are used in the detection of outliers and period in time series analysis.

5.2. Adaptive Filtering, Prediction and Control

Filtering is concerned with the extraction of signals from noise. Prediction is concerned with the problem of extrapolating a given time series into the future. Control is concerned with the manipulation of the inputs to a system so that the outputs achieve certain specified objectives. The term "adaptive" is used in the design techniques that are applicable when the system model is only partially known. These techniques will incorporate some form of on-line parameter adjustment scheme (Goodwin et al. [1984]).

Adaptive and recursive methods were studied by Cohen (1963), Bossons (1966), Ogata (1967), Trigg et al. (1967), Wiberg (1971), Morrison et al. (1977), Ledolter (1979), Gardner et al. (1980), Ljung (1983,1987), Meinhold et al. (1983), Kahl et al. (1983), Goodwin et al. (1984), Graupe (1984), Sholl et al. (1984), Louv (1984), Spall et al. (1984), Sastri (1985a,b,1988), Broemeling et al. (1985), Hannan et al. (1989), and Steigerwald (1992).

5.3. Multivariate Time Series

The time series data in advanced automated manufacturing consist of observations from several variables. In this section we introduce a more general class of multivariate time series models to describe relationships among several time series variables. A useful class of parsimonious models is the multivariate ARMA(p,q) process

$$\Phi_p(B)x_t = \theta_q(B)a_t$$

where $\Phi_p(B) = \Phi_0 - \Phi_1 B - \Phi_2 B^2 - \cdots - \Phi_p B^p$ and $\theta_q(B) = \theta_0 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ are the autoregressive and moving average matrix polynomials at orders p and q, respectively, and Φ_0 and θ_0 are nonsingular m × m matrices. For any nondegenerate case where the covariance matrix Σ of a_t is positive definite, we assume in the following discussions, with no loss of generality, that $\Phi_0 = \theta_0 = I$, the m × m identity matrix (Wei [1990]).

Multivariate ARMA models were considered by Jenkins et al. (1981), Solo (1984), Lewis et al. (1985), Jeon et al. (1988), Byrne (1988), Peiris (1988a,b,1990), Saikkonen et al. (1988,1989), Tiao et al. (1989), Mittnik (1990), Wei (1990), and Brockwell et al. (1990).

Multivariate spectral models were studied by Taniguchi et al. (1987) and Nakano et al. (1987).

6. Concluding Remarks

This paper proposed three dimensions for classifying control charts and reviewed the recent developments. As the technology of manufacturing involves toward more automated processes, roles of control charts will be very important. The theory of control charts and its applications will prosper on the ground that the computer is available everywhere, which is an essential part to plot and to calculate difficult statistic.

In advanced automated manufacturing, adaptive and multivariate stochastic control charts may be a great role.

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