Statistical Analysis of Profile Monitoring

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# Statistical Analysis of Profile Monitoring

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# Preface

The aim of this book is to summarize major achievements in statistical profile monitoring methods. Statistical profile monitoring can be considered as a potential subarea of statistical quality control that has recently attracted attention of many researchers and practitioners. One major reason behind this attractiveness is the wide range of applications that one can identify for the concept of profile monitoring in different service and manufacturing settings. It should not be too long before the concept, methods, and issues related to statistical profile monitoring and its related analyses are introduced in different engineering and statistical textbooks and software packages.

It is well known that, in standard statistical process control applications, one is traditionally concerned with monitoring performance of a process or product using measurements on a single quality characteristic or a vector of quality characteristics at a given time or space. However, in many applications of statistical process control, quality of a process or product is best characterized and summarized by a functional relationship. In the literature of profile monitoring, this functional relationship is usually referred to as profile, signature, or waveform. Fortunately, advances in technology have made it possible for process or statistical engineers and practitioners to collect a large number of process or product measurements to reconstruct this functional relationship with the aim of understanding and evaluating its stability over time using statistical methods.

This book addresses the fundamental concepts, methods, and issues related to statistical profile monitoring. The book begins with an introduction to the concept of profile monitoring and its applications in practice, and then throughout the remaining nine chapters, issues related to simple linear profiles, complex nonlinear profiles, and roundness profiles or profiles associated with geometric specifications are discussed.

This book can be used as a major reference or textbook for researchers, engineers, and statisticians who are interested in advanced topics in statistical process control. In addition, this book can serve as a major reference for senior undergraduate students who are familiar with the basic concepts and methods of statistical process control or graduate students in advanced quality control course.

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CHAPTER 1

# Introduction to Profile Monitoring

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## INTRODUCTION

Quality can play an important role in the success and prosperity of many manufacturing and service organizations. A company that can fulfill customers' needs on time, with competitive cost and superior quality, can easily dominate its competitors. Hence, it is logical for organizations to view quality as business strategy. International Organization for Standardization (ISO) provides a comprehensive definition of quality in its ISO 9001:2008 quality management systems. According to this standard, quality is defined as "the degree to which a set of inherent characteristics fulfills requirements." However, Montgomery (2009) and others define quality as inversely proportional to variability. This modern definition of quality implies that variability reduction in the key quality characteristics should be of prime concern to practitioners.

Different quality improvement and variability reduction tools and methods exist that one can employ in practice to improve process performance. Statistical process control (SPC), a subarea of statistical quality control (SQC), is one of the improvement methods that can be effective in practice. SPC consists of a set of powerful tools that helps practitioners to improve quality of products and services by achieving process stability and reduction of process variability. SPC includes seven major problem-solving tools, which can be employed to improve quality. These tools, which often are referred to as "the magnificent seven", are as follows:

*Statistical Analysis of Profile Monitoring*, First Edition. Edited by Rassoul Noorossana, Abbas Saghaei and Amirhossein Amiri.

1. Histogram or stem-and-leaf plot
2. Check sheet
3. Pareto chart
4. Cause-and-effect diagram
5. Defect concentration diagram
6. Scatter diagram
7. Control chart

Among these seven tools, control chart is often viewed as a featured tool of SPC. Since its introduction by Walter A. Shewhart in 1924, control charts have been applied to processes in different manufacturing and service industries. Control chart is a helpful tool that plots measurements of a quality characteristic against time or sample number with the aim of distinguishing random, common, or chance causes of variation from the assignable causes of variation. Chance causes of variation are inherent natural variability of the process and are a cumulative effect of many inevitable small causes. Montgomery (2009) refers to this natural variability as "background noise." A process that operates only in the presence of chance causes or background noise is said to be statistically in-control. On the other hand, variability arising from other sources of variation such as materials, personnel, machines, environment, measurement system, and methods when compared to chance causes of variation are larger and will eventually move process to an unacceptable level of performance with respect to the quality characteristic of interest. Montgomery (2009) and others refer to these sources of variability as assignable or special causes of variation. According to Deming (1982), special causes of variation refer to "something special, not part of the system of common causes." A process that operates in the presence of assignable causes is said to be statistically out-of-control. Figure 1.1 illustrates the chance and assignable causes of variation in a process at different times. Except the first case where process operates in-control, the other cases indicate presence of assignable cause(s) leading to an out-of-control condition. Presence of an assignable cause will be eventually detected by a control chart when an unusual point or pattern appears on a control chart.

A typical Shewhart control chart is shown in Figure 1.2. A Shewhart control chart consists of a center line and symmetric upper and lower control limits. The center line is the center of gravity for the observations or the place where most of the observation should fall if process operates only in the presence of chance causes of variation. The upper and lower control limits that show the acceptable region for the sample statistic are determined using statistical considerations.

A fundamental assumption in any Shewhart control chart is that the plotted statistic should be computed on the basis of independently and identically distributed random variables. Departure from these premises may significantly affect the performance of control charts. Control charts, based on the type of quality characteristic, can be divided into two general categories of variable and attribute control charts. The quality characteristics used in the variable control charts are measured on continuous scale. Length, temperature, and weight are examples of measurements made in continuous

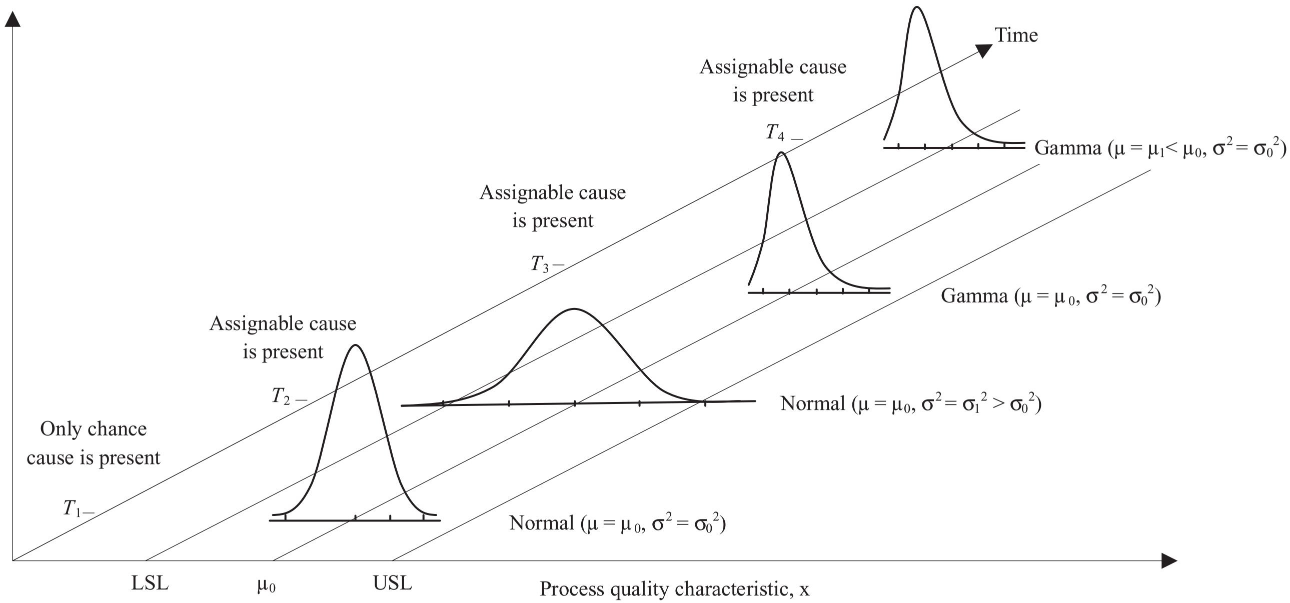


**Figure 1.1** A process in the presence of chance and assignable causes of variation.

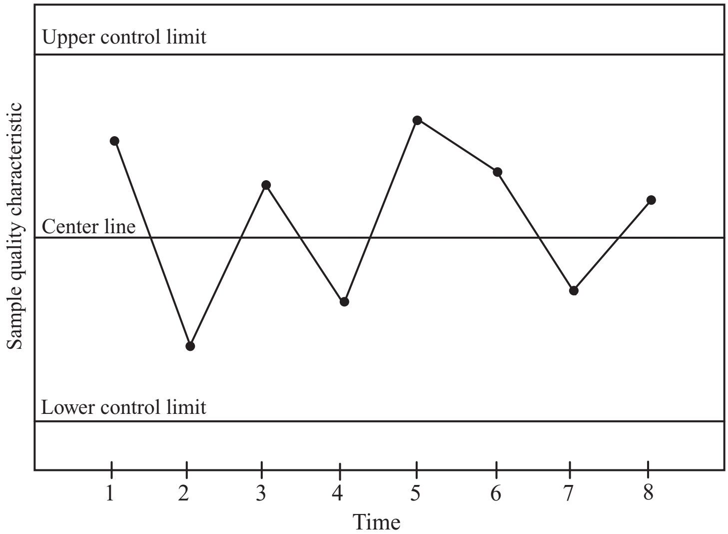


**Figure 1.2** A typical control chart.

or measurable scale. However, attribute control charts are based on quality characteristics, which can only take certain integer values or can only be expressed in discrete or countable scale. Number of conforming products in a shipment, surface defects on a product, and patients arriving at an emergency room of a hospital with a trauma during a day are examples of measurements made in discrete or countable scale. A concise classification for univariate control charts based on continuous and discrete scales of measurement and correlation status between observations is provided by Montgomery (2009). This classification of control charts is presented in Figure 1.3.

In control charting, it is important to distinguish between Phase I or retrospective phase and Phase II or prospective phase analyses. According to Woodall et al. (2004) and others, in Phase I analysis of control charting, a set of historical process data is used to study process variation and evaluate its stability over time. In phase I, after identifying and eliminating anomalous observations and verifying process stability, process performance is modeled and unknown parameters are estimated. Retrospective analysis of Phase I allows one to construct trial control limits and determine if the process has been in-control when historical set of observations were collected. In Phase II analysis, one is concerned with process monitoring and detecting out-of-control conditions using online data to quickly identify shifts in the process from the trial control limits constructed in Phase I to determine if the process is under statistical control.

In standard SPC applications, one is traditionally concerned with monitoring performance of a process or product considering measurements on a single quality characteristic or a vector of quality characteristics at a given time or space. However, advances in technology have allowed engineers and practitioners to collect a large

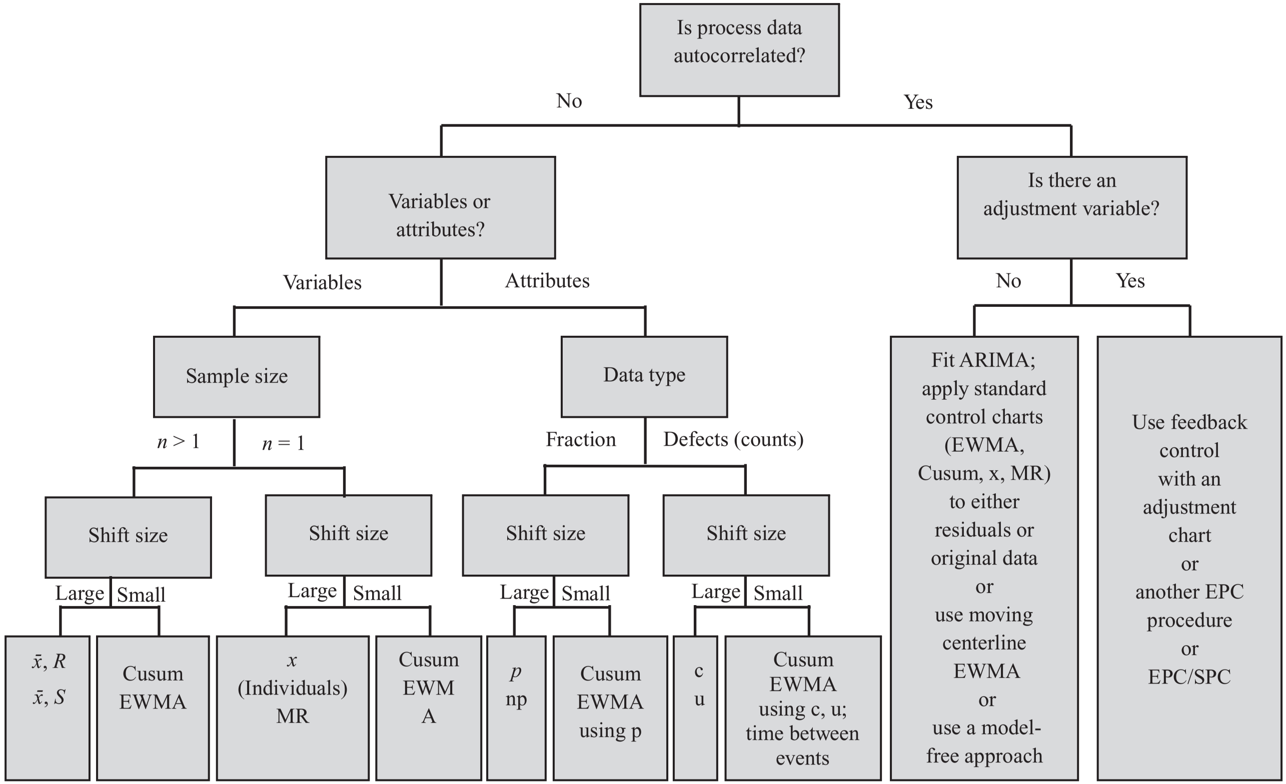


**Figure 1.3** Classification of univariate control charts. (Adapted from Montgomery 2009.)

number of process or product measurements to reconstruct the entire functional relationship for the process or product performance. This functional relationship is usually referred to as a profile, signature, or waveform. For each profile it is assumed that $n$ values of the response variable are measured along with the corresponding values of one or more explanatory or independent variables.

Section 1.1 presents several examples where quality of a process or product is better characterized and modeled by a profile rather than measurements on a single quality characteristic or a vector of quality characteristics.

## 1.1 FUNCTIONAL RELATIONSHIPS QUALIFIED AS PROFILES

Profiles can be used in many different manufacturing and service areas to evaluate product or process performance over time or space. In this section, we discuss practical situations where a profile can effectively represent or characterize a product or process performance.

### 1.1.1 Calibration Applications

Profile monitoring has extensive applications in calibration of measurement instruments. This is to ascertain their proper performance over time, determine optimum calibration frequency, and avoid overcalibration. Croarkin and Varner (1982) proposed a monitoring scheme initially developed to address calibration issues in optical imaging systems. Their proposed scheme requires plotting deviations of the measured values from the standard values on a Shewhart control chart for lower, middle, and upper values of the standards. In the calibration process, it is assumed that the measured values are related to the standard values through the following relationship:

$$y_{ij} = f(x_i) + \varepsilon_{ij}, \quad i = 1, 2 \ldots n, \quad j = 1, 2 \ldots, \tag{1.1}$$

where $y_{ij}$ are the measured values, $x_i$ are the standard values, $n$ is the number of observations in the $j$th random sample, and $\varepsilon_{ij}$ are the error terms assumed to be independent and identically distributed (i.i.d.) normal random variables with mean zero and variance $\sigma^2$. This scheme is now part of the ISO 11095, “Linear Calibration Using Reference Material.” Figure 1.4 depicts the relationship between the measured values and the standard amounts.

### 1.1.2 Artificial Sweetener

Kang and Albin (2000) discussed the case of aspartame, an artificial sweetener, where the amount of aspartame that can be dissolved per liter of water ($y_i$) is a function of temperature ($x_i$). Figure 1.5 shows the milligrams of aspartame dissolved per liter of water for several samples. This figure indicates that as temperature increases, the amount of aspartame dissolved per liter of water increases up to a certain level and then drops. This pattern appears form sample to sample and according to the profile

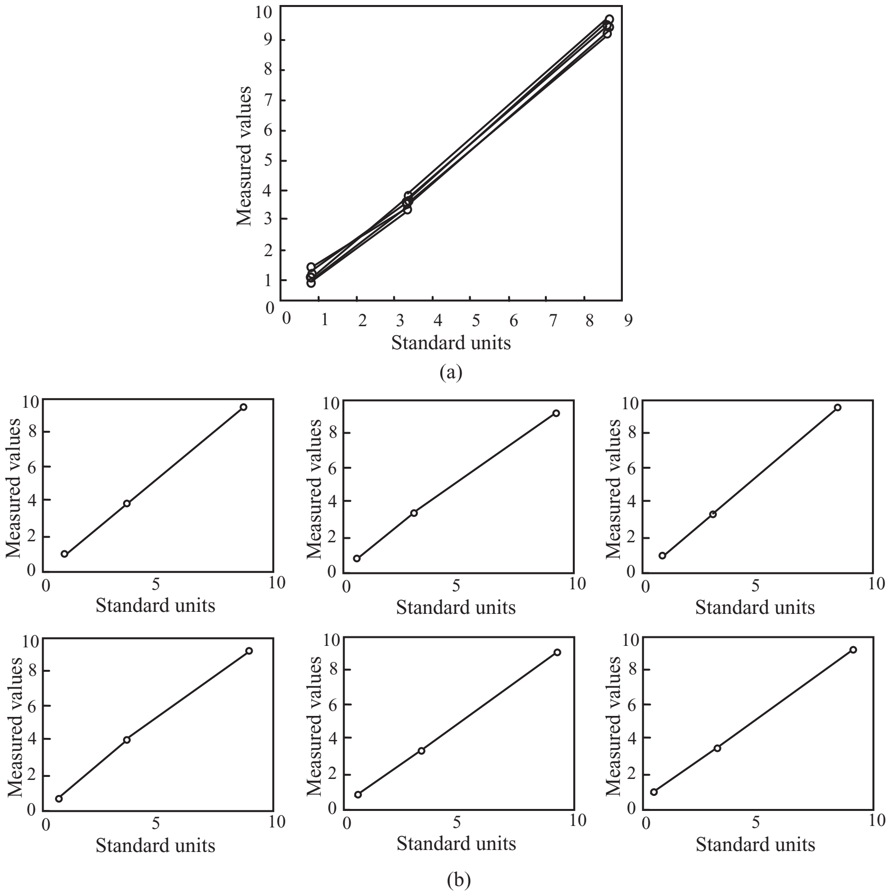


**Figure 1.4** Plot of the line width reference standards (in upper, middle, and lower ends of measurement range) versus the measured values in (a) all samples in one figure (b) samples in separate figures.

of the process at different sampling period one needs to decide about the status of the process.

### 1.1.3 Mass Flow Controller

Kang and Albin (2000) considers mass flow controller (MFC) as an example where monitoring a profile is preferred technically over monitoring a single measurement over time. MFC is a device that controls flow of gases in a gas chamber during the semiconductors manufacturing operation, where photoresist is etched away and the required patterns for the layer of chips is created. This device includes four main components: (1) a bypass, (2) a sensor, (3) an electronic board, and (4) a regulating valve. The measuring side contains the bypass, sensors, and one part of electronic

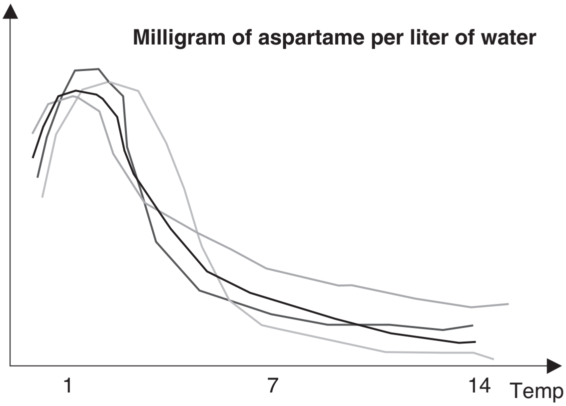


**Figure 1.5** Aspartame profiles. (Adapted from Kang and Albin 2000.)

board. The other elements form the controlling side. A schematic view of MFC is shown in Figure 1.6.

Since MFC plays an important role in this semiconductor manufacturing process, performance of this device should be evaluated constantly. The common practice in evaluating performance of the MFC device is to break into the gas lines and recalibrate the device at regular intervals, which takes approximately 4 hours. According to Sheriff (1995), "a \$1500 MFC device may cost more than \$250,000 in production downtime during its six or seven-year life time." Hence, an SPC scheme that helps to eliminate unnecessary recalibrations of the device by differentiating assignable causes from random causes could lead to significant process improvement and annual savings. Kang and Albin (2000) provide an effective statistical process monitoring

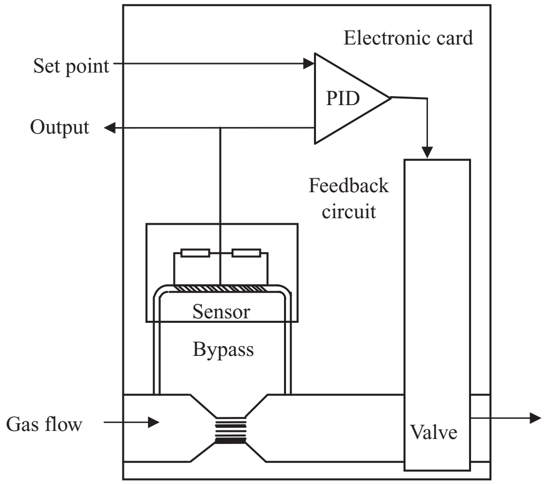


**Figure 1.6** Schematic of MFC.