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:
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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
Process quality characteristic, $x$

- **Assignable cause is present**
- **Gamma** ($\mu = \mu_1 < \mu_0, \sigma^2 = \sigma_0^2$)
- **Normal** ($\mu = \mu_0, \sigma^2 = \sigma_0^2$)
- **Normal** ($\mu = \mu_0, \sigma^2 = \sigma_1^2, \sigma_1^2 > \sigma_0^2$)
- **Gamma** ($\mu = \mu_0, \sigma^2 = \sigma_0^2$)
- **Only chance cause is present**

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

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

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
FUNCTIONAL RELATIONSHIPS QUALIFIED AS PROFILES

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
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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
scheme, which compares performance of the device represented by a linear profile to the theoretical linear profile that exists between the response and the explanatory variables. Figure 1.6 depicts the linear relationship between the response or measure pressure and the explanatory variable or flow rate.

According to Kang and Albin (2000), removal of the etcher and evaluation of the MFC performance through collection of the required observations only takes around 20–30 minutes, which is a significant reduction in time. Section 1.1.4 briefly presents several examples where profiles, signatures, or waveform signals can be used to well model performance of a process or product.

1.1.4 Vertical Density

Walker and Write (2002) considered vertical density data from engineered wood board that contain particleboard and medium density fiberboard. The vertical density is measured at certain depth across the thickness of the wood board. The measurements on a sample form the vertical density profile, which is of a bathtub shape. In other words, the wood density is higher on the top and bottom surfaces and drops as we get close to the middle section. Each vertical density profile consists of $n = 314$ measurements taken 0.002 in apart. Figure 1.7 illustrates the vertical density measurements $(y_i)$ as a function of depth $(x_i)$ for several wood boards.

1.1.5 Engine Torque

Amiri et al. (2010) described an example in automotive industry where profiles of polynomial form were applicable. The relationship between the torque produced by
an automobile engine and the engine speed in revolution per minute is an important quality characteristic that needs to be monitored in order to distinguish conforming engines from nonconforming ones. Conforming engines ought to yield polynomial profiles very close to the theoretical engine profile, which is well described by a second-order polynomial model. Figure 1.8 illustrates the engine torque data for 26 engines as a function of engine speed in revolution per minute. For each engine, the torque value is measured at 14 different engine speeds.

1.1.6 Stamping Force

Jin and Shi (1999) studied process performance in a stamping operation. In this operation, stamping tonnage sensors are usually used to measure the stamping force for each stamped part. Figure 1.9 shows the total tonnage or stamping force \( y_i \), which is the sum of the outputs of all tonnage sensors mounted on the press, as a function of the crank angle \( x_i \). A complete stamping cycle covers crank angles from \( 0^\circ \) to \( 360^\circ \), which can be divided into different segments according to different forming stages of a stamping process. This complex “waveform signals” as the authors refers to or profiles can be used to identify any potential process failures in different forming stages.

1.1.7 Location Chart

Boeing (1998) proposed location control chart for situations when several measurements of the same variable are made on each manufactured part. Although one can include this situation in the profile framework and analyze the data accordingly, but
the solution proposed by Boeing (1998) is based on control limits for each location. These control limits depend only on the responses measured at that location and the multivariate structure of the data is obviously ignored. Figure 1.10 shows a location chart where the response variable is the upper flange angle measured at \( n = 15 \) different locations for 13 parts.

### 1.1.8 Acceptance Sampling Application

Tsong et al. (1997) developed an acceptance-sampling rule based on dissolution profiles of pharmaceutical products such as tablets that require long dissolution time. The acceptance rule requires fitting a dissolution profile to tablets of the approved
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1.1.8 geometric Profile

Geometrical profiles such as roundness, flatness, and cylindricity can be considered as a natural extension of two-dimensional profiles. Gardner et al. (1997) used spatial
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![Graph showing spatial profiles for wafer surfaces](image)

**Figure 1.12** Spatial profiles for wafer surfaces (a) with no equipment faults and (b) with known equipment faults. (Adapted from Gardner et al. 1997.)

Information to model spatial signatures or profiles of wafer surfaces. Their methodology consists of modeling and comparing observed wafer surfaces to a baseline wafer surface to detect and diagnose various types of equipment faults. The response variable in their study was defined as the gate oxide thickness and the explanatory variables were defined as the $x$ and $y$ distances from the center of the wafer. Figures 1.12a, b illustrate the spatial profiles for gate oxide thickness produced under a fault-free condition and known equipment failures, respectively.

1.2 FUNCTIONAL RELATIONSHIPS NOT QUALIFIED AS PROFILES

In most practical applications of SPC, a univariate quality characteristic or a vector of quality characteristics is used to evaluate performance of a process or product. However, there exist situations where quality of a process or product can be well characterized by a profile. Although these situations appear to be increasingly common in practice, but there exist occasions where a functional relationship looks very much like a profile but in fact it is not really a profile. Woodall (2007) believes that most of situations where functional relationship cannot be considered as profile involve applications where times series data are collected on individuals while time
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1. Local constant
2. Local constant w/ Outliers
3. Local constant w/ Change Points
4. Local trend
5. Local trend w/ Outliers
6. Local trend w/ Change Points
7. Growth
8. Recent changes
9. High volatility

Figure 1.13  Customer telephone usage patterns (cross) with moving average smoothing (solid line) and global linear regression fit (dashed line). (Adapted from Jiang et al. 2007.)

index remains the same. As an example of profile that involves time series data with differing time index, he refers the force of an automobile air bag on the passenger since its deployment as a function of time.

Jiang et al. (2007) presents the concept of business activity monitoring (BAM) and points out that real-time BAM begins with profile monitoring. They discuss the case of monthly customer telephone usage in a telecommunications company from October 2001 to September 2003 and consider it as an example of profile. Figure 1.13 illustrates these patterns of monthly telephone usage for nine different customers. Although the shape of the time series data may look like a profile but certainly under the definition provided by Woodall (2007), their time series data on customer telephone usage would not be qualified as profile.

Brown et al. (2004) consider the case where data collected on cross-section of paper during manufacture are broken into different segments, and a stochastic model or a profile is fitted to each segment. Then estimated model parameters are used as inputs into multivariate quality control charts to monitor the manufacturing process. It is obvious that this is the case of multiple time series observations that are interpreted as successive profiles, and since only one time index exists then this example again would not be qualified as profile.
1.3 STRUCTURE OF THIS BOOK

The purpose of this section is to provide a broad overview on the structure of the book to help reader to better understand the structure of the book and what one should expect in each chapter.

1.3.1 Chapter 2

In many calibration applications, the functional relationship between the measured and real values is given by a simple linear regression model. Obviously, in these situations simple linear profile monitoring techniques could be used to establish a control scheme. Chapter 2 is devoted to Phase I and Phase II control charting methods for monitoring simple linear profiles. The calibration problem in the optical imaging systems can be considered as a representative example of such profiles. Another helpful example on simple linear profile is introduced by Mestek et al. (1994). The main focus of this example is to study the calibration curves in the photometric determination of Fe$^{3+}$ with sulfosalicylic acid. Detailed description about this example is also provided in this chapter.

1.3.2 Chapter 3

In certain cases, quality of a process or product can be well characterized by a multiple linear or polynomial profile. In Chapter 3, several approaches for monitoring such profiles are discussed. Zou et al. (2007) present a motivating example in semiconductor manufacturing. In this example, the quality characteristic to be monitored is the profile of trenches associated with deep reactive ion etching process, which is a key process in microelectromechanical systems fabrication operation. In this process, a trench with vertical and smooth sidewalls can be regarded to have an ideal profile. However, negative and positive profiles that are associated with overetching and underetching, respectively, are considered unacceptable. Figure 1.14 illustrates various types of trenches.

It is obvious that the entire profile cannot be represented by a polynomial or a general linear profile. Since information contained in the left and right corners, which are symmetric, would allow one to evaluate process performance; hence, it would suffice to consider only the profile associated with one side of the trench to establish a control scheme. If the corner is rotated 45° counterclockwise then a quadratic

![Figure 1.14](image-url)  

**Figure 1.14** Negative, positive, and desired profiles. (Adapted from Zou et al. 2007.)
1.3.3 Chapter 4

Profile monitoring applications are not restricted to regression models with continuous response variables. In many practical applications, quality of a process or product can be well characterized by a binary response variable in the form of conforming or nonconforming product. For instance, Yeh et al. (2009) discuss the case of compressive strength of an alloy fastener originally discussed by Montgomery et al. (2006). In this example, the compressive strength of alloy fastener used in aircraft manufacturing is considered as a critical-to-quality characteristic, which is tested at particular load to examine whether it will fail or stand the load. Under this condition, the profile of interest consists of a response, which is a binary variable and an explanatory variable (load strength), which is continuous in nature. They use logistic regression model to develop control charting techniques suitable for monitoring profiles with binary responses. Chapter 4 focuses on profile monitoring techniques suitable for binary response profiles. Healthcare, public health surveillance, and hospitality industries are among the industries where profiles with binary or categorical response variables are encountered easily. As an example, in healthcare and public health surveillance, one considers the mortality rate after a cardiac surgery. It is important to note that that mortality rate depends on many variables, including age, diabetic status, and Parsonnet score.

1.3.4 Chapter 5

There are many instances where performance of a process or product can be well modeled by a nonlinear relationship. To handle monitoring issues related to such situations, one can use either parametric nonlinear regression or nonparametric smoothing methods. The purpose of parametric nonlinear profile monitoring is to reduce the complex nonlinear profile into a few parameters through the nonlinear model estimation and then form a control chart scheme on the estimated parameters of each individual profile. The parametric nonlinear regression approach and its associated control schemes are the main subject of this chapter. A vertical density data of the
wood board presented in Figure 1.7 of Section 1.2.3 is a typical example of a nonlinear profile.

1.3.5 Chapter 6

A main assumption in profile monitoring using parametric models is that the data follows a particular assumed parametric form. It is obvious that there exists many occasions where this assumption fails to hold. In other words, the observed profile $f$ cannot readily admit to a parameterization using a parametric functional relationship. Under such conditions, a more general form of the profile that allows for a nonparametric representation of the relationship would be appropriate. The vertical density profile data from Walker and Wright (2002) is considered in this chapter to evaluate performance of the nonlinear profile monitoring methods.

1.3.6 Chapter 7

Parker et al. (2001) provide a calibration example respecting the force balance in the wind tunnel experiments at NASA Langley Research Center. Three orthogonal force components representing response variables and three orthogonal torque components respecting explanatory variables are measured simultaneously. Figure 1.16 illustrates these components. A close look of the variables involved indicates that this is the case of a multivariate multiple linear profile because of the correlation structure that exists between the response variables. It is obvious that if the correlation structure between the response variables is ignored by assuming separate profiles then misleading results should be expected. This chapter provides various approaches for Phase I and Phase II monitoring of multivariate multiple and multivariate simple linear profiles.

Figure 1.16  A schematic view of forces and moments. (Adapted from Parker et al. 2001.)
1.3.7 Chapter 8

In the SPC-related literature, there are various cases in which we are interested in monitoring geometric specifications of products. Roundness, flatness, straightness, or cylindricity of products could be examples of such quality characteristics. It is obvious that under such circumstances, one would be interested in detecting any departure from the baseline shape of the product. Figure 1.17 shows various types of nonconforming shapes for a machined cylinder discussed by Henke et al. (1999) and Zhang et al. (2005). Detailed discussions on the methods for monitoring quality characteristics related to the geometric specifications of manufactured products are presented in this chapter.

1.3.8 Chapter 9

Staudhammer et al. (2007) consider a case where thickness of lumber is a function of the distance on the board. The relationship between the lumber thickness and the distance is presented in Figure 1.18. A close analysis of the patterns on this figure indicates that observations within each profile are not independent and as
a result a fundamental assumption of profile monitoring approaches is violated. Violation of this assumption if not addressed properly would significantly affect the performance of the approach used to monitor processes that inherently generate autocorrelated observations. This chapter addresses various issues related to both within- and between-profile autocorrelations and several approaches for monitoring profiles when the independence assumption is violated are discussed.

1.3.9 Chapter 10

There are many instances where a parametric linear or nonlinear model may not well represent a profile. In practice, process engineers may want to avoid spending too much time on fitting a parametric model to a set of data representing a complicated profile. In such cases, if an appropriate right parametric nonlinear regression model is not selected to represent the complex profile then misleading results should be expected. Zou et al. (2008) refer to the asymptotic normal distribution of the estimators that may significantly affect the in-control and out-of-control performance of parametric-based control schemes, slow convergence rate of the iterative procedures, and having a similar form for the in-control and out-of-control models as potential problems that one may encounter while working with nonlinear regression models. In this chapter, assuming that a profile can be well represented by a regression function, several nonparametric methods such as spline and wavelet methods are discussed, which help to address issues when data does not follow a particular parametric form.

REFERENCES


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