
Chapter 22 Quality Control



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22.1 A Short History of Quality Control

22.2 Control Charts for Individual Observations (Run Charts)

22.3 Control Charts for Measurements: $\bar{X}$ and R Charts

22.4 Actions for Out-of-Control Processes

22.5 Control Charts for Attributes: p Charts and c Charts

22.6 Philosophies of Quality Control

Sony

In 1945, at the end of World War II, Masaru Ibuka started a radio repair shop in a bombed-out building in Tokyo. The next year, Akio Morita joined him and together they founded a company called Tokyo Tsushin Kogyo K.K. (or Tokyo Communication Engineering Company), which built Japan's first tape recorder. In the early 1950s, Ibuka traveled to the United States and convinced Bell Labs to license its transistor technology to his Japanese company, which then released Japan's first commercially produced transistor radio. The next May, the company released a new radio with a slim design and

improved sound quality. In 1957, it came out with the TR-63—the smallest transistor radio in commercial production. By all accounts, it was a worldwide commercial success.

With increasing international sales, Ibuka and Morita knew they needed a simpler name for their company. Unfortunately, the name Totsuko didn't work well in English, and their initials, TKK, were already in use by a railroad company, so Ibuka and Morita worked to find a word that didn't exist in any language but would be easy to remember. Finally, they combined the Latin word for sound, *sonus*, with the American word *sonny*, which was a popular word meaning boy or young man in the 1950s. From this Sony was born in 1958.

Sony is now one of the world's most recognized brands with sales of more than \$57 billion for the fiscal year ending March 31, 2013. It employs more than 146,000 people worldwide.

Unfortunately for the young Sony Corporation, in the 1950s, the phrase "Made in Japan" was synonymous with cheap and shoddily made. Japan's manufacturing capabilities had been destroyed in the latter part of World War II. To rebuild its economy as quickly as possible, Japan started producing and exporting large quantities of inexpensive goods, including electronic products. A rumor often heard in the United States after the war was that Japan had renamed one of its towns Usa so that it could stamp "Made in Usa" on its products. Although this urban legend was false (in fact the town of Usa on the island of Kyushu existed long before WWII) the shoddy quality of the Japanese goods gave credence to the story and kept it alive for years.

The United States sent General Douglas MacArthur to oversee the rebuilding of Japan after the war ended. Realizing the importance of reversing Japan's poor quality image, he recruited two key players, W. Edwards Deming and Joseph Juran, who had both been active in the field of quality control in the United States. In addition, he enlisted the help of Homer Sarasohn to help rebuild the communication infrastructure of Japan.

Just after World War II, Japanese manufacturing plants were designed to produce radios using vacuum tube technology. In early trial runs, Sarasohn was shocked to find that yields were commonly less than 10%. In other words, 90% of the vacuum tubes produced were defective. Even more shocking was that the Japanese were not surprised and had little understanding of quality; other than the Zero fighter (known as the best carrier-based fighter jet in the world at that time), their engineering designs were often flawed with low production yields. Sarasohn decided to work more closely with the plant managers on improving quality at their plants.

One day, Sarasohn made a visit to the Tokyo Communication Engineering Company, a new start-up factory that was building radio equipment because equipment owed to Sarasohn was overdue. When he arrived at the factory, he found chaos. When the owners (Ibuka and Morita) heard of the surprise inspection, they raced to see Sarasohn in Tokyo, who gave them one more chance to prove that they could learn

something about quality and apply it to their factory. Luckily Ibuka and Morita learned their lesson, and this young company was the company that eventually changed its name to the Sony Corporation.

These quality control efforts in Japan proved enormously fruitful. In the 30 years after WWII, Japan became a world leader in manufacturing, and today Japanese products consistently rank among the world's highest quality. The United States, the world leader in quality in the 1950s, saw its market share in electronics and automobiles shrink at the expense of Japan in this same time period.

Today, manufacturing has shifted from Japan, Germany, and the United States to China. In 2006, China replaced the United States as the world's largest exporter. Unfortunately, quality control issues often plague Chinese manufacturing. News stories about baby formula and pet food tainted with melamine, toys painted with lead paint, and tires that fail at high speed alarm consumers worldwide. The head of China's top quality-control agency quit in the midst of the scandal about tainted milk in 2008. Quality control continues to be of vital importance to worldwide manufacturing.

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22.1 A Short History of Quality Control

The desire to make quality products is part of human nature. Several millennia ago, the builders of the Great Pyramid of Giza had to produce blocks of incredible uniformity to build a pyramid whose four sides were perpendicular to within 3.5 arc seconds. During the Middle Ages in Europe, guilds were formed, in part to enforce quality control on craftsmen but also to punish those who tried to pass off inferior goods. The manufacture of money has long relied on quality control to guarantee that the same amount of precious metal is used in each coin. In seventeenth century England, Samuel Pepys wrote in his famous diary of his inspection of quality at The Royal Mint.

Statistical methods for quality control were pioneered in the 1920s at the Bell Telephone Laboratories in the United States (where they were used in producing telephone equipment at the company's Western Electric subsidiary) and at roughly the same time at the General Electric Company in the United Kingdom. Quality control today is a tool in the larger effort of continual process improvement in both the manufacturing and service industries. In this view, work is a process on which data can be gathered and studied. This study can then lead to improvement in the process, which ideally will have an impact on both customer satisfaction and the company's bottom line. The process improvement strategy includes understanding the process, collecting the data, assessing the process, eliminating causes of variation, studying the cause and effect of relationships within the process, and implementing changes. In this chapter we will study some tools used in the assessment of the process data to investigate whether the process has changed, either in its mean or in its variation.



Walter A. Shewhart (1891–1967) was an early pioneer of quality methods. Before his arrival at the Western Electric Company, quality control consisted of inspecting products and removing defective items. Shewhart introduced statistical methods including the quality control chart which bears his name.

Walter A. Shewhart was a statistician and engineer working at Bell Laboratories in the early part of the twentieth century, responsible for improving the quality of the manufactured telephones. As early as 1924, he introduced a chart in an internal Bell Labs memo to graphically display variation in a process over time. The kind of chart he used, a time plot of a measure of quality, became known as a **control chart** ⓘ, or sometimes a **Shewhart chart** ⓘ, in his honor. In the same memo, he defined the fundamental rule of **statistical process control (SPC)** ⓘ: “Variation from common-cause systems should be left to chance, but special causes of variation should be identified and eliminated.”

Shewhart's insight was that the variation we see in manufacturing arises from two distinct sources. Some of the random fluctuations are *intrinsic* to the process or **common-cause variation** ⓘ. Others, which are not, are called **special-cause variation** ⓘ. When special-cause variation is present, the process is said to be **out of control** ⓘ. The short-term focus of quality control is to detect and correct the special causes of variation. The long-term focus of continual quality improvement is to reduce the amount of variation from the common causes. Shewhart suggested a system of analysis based on the scientific method specifically to address the special-cause issue, but which has also been used as the basis for continual quality improvement.

The term *control chart* is somewhat of a misnomer. Certainly one can't control a process simply by graphing measurements of it over time. The term *quality control* became popular in the latter part of the twentieth century and control charts were an important tool in the quality control effort. More recent views of process improvement view the process as evolving toward higher and higher quality (and less variation) and so the term quality “control” is almost passé. The American Society for Quality Control (ASQC) changed its name in the 1980s to the American Society for Quality (ASQ) when its members realized that their methods could be part of a more general movement toward excellence in the organization.



Because he helped Japanese industrial leaders rebuild after World War II and to shed the image of Japanese products as cheap and shoddy, W. Edwards Deming (1900–1993) is known as the father of the Japanese postwar industrial revival. He was also regarded by many as the leading quality guru in the United States until his death in 1993.

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In 1950, when W. Edwards Deming replaced Sarasohn in Japan, he taught the Shewhart principles and process to Japanese managers. The process became codified into four distinct stages: Plan, Do, Check, and Act—known as the PDCA cycle (**Figure 22.1** ⓘ). In the *Plan* stage, the manager identifies and describes the process to be improved and suggests improvements. In the *Do* stage, the manager implements on a pilot level the improvement strategies. In the *Check* stage, the manager examines variation to see if the improvement strategies have been successful. Finally, in the *Act* stage, depending on the

results of the Check stage, the manager implements the improvement strategies on a large scale. These stages are completed continuously and repeatedly, so that they form a cycle, or some say a spiral, of quality improvement.¹

¹Some organizations use a modification of this known as the Define-Measure-Analyze-Improve-Control (DMAIC) cycle.

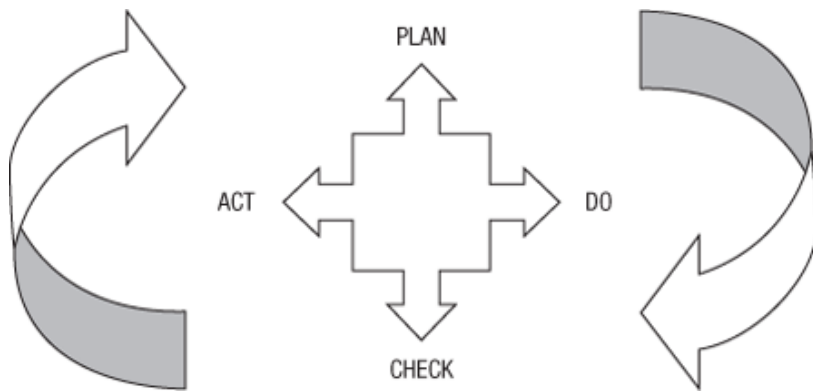


Figure 22.1

The Shewhart PDCA cycle.

Walter Shewhart's Impact

Walter A. Shewhart is considered to be the true father of modern quality control and was actually Sarasohn's first choice to continue his work in Japan in 1950. However, he was in poor health, so Deming was invited to Japan to continue the education of Japanese managers. Shewhart summarized his concepts in quality control in his textbook *Statistical Method from the Viewpoint of Quality Control*, published in 1939, in which he focused on applications to mass production and described the three steps of quality control: specification, production, and inspection. According to Shewhart, the rise of standardization in the early to mid 1900s created a need to balance the objectives of (1) minimizing the number of defectives, or rejected parts, and (2) minimizing the cost of inspection.

Control and Specification Limits

Shewhart's idea for monitoring the variability in a process was based on probability theory. He knew that if the common-cause variation in a process was Normally distributed, there would be only a small probability that an individual value could be farther than certain limits from the mean. To monitor the process, Shewhart advocated plotting measurements of the process over time, looking for evidence that the process might change and slip "out of control." He called such a plot a control chart, although they are often referred to as Shewhart charts. Typical examples of measurements for manufactured parts are characteristics such as thickness or size, weight, color, or electrical properties, just to name a few possibilities. Before starting to monitor the process, however, the process must first be stable, or "in control"—that is, both the mean and the standard deviation must be constant. Then, if an observation deviates far enough from the mean, it could be taken as a signal that either the process mean or standard deviation has changed.

Figure 22.2 shows a control chart for 15 observations from an automobile manufacturing plant. The measurements are the diameters of a bolt used to fasten the car door to the chassis. The desired mean of the bolts' diameters is 23 mm:

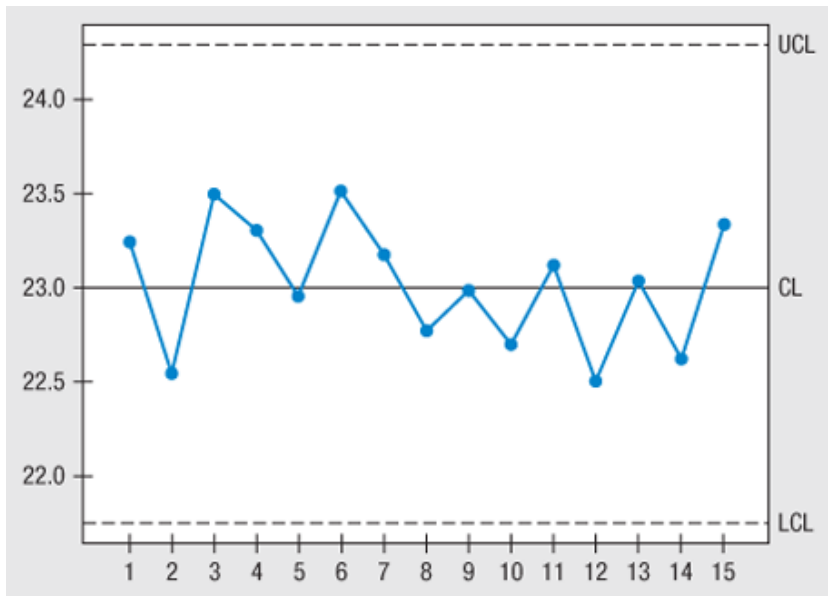


Figure 22.2

A control chart for 15 diameters of bolts with a desired mean of 23 mm.

The main idea of using a control chart to monitor a process is that if the process stays in control, observations will stay within a certain distance of the mean (at least with very high probability). However, if the process mean or standard deviation changes, then the observations will start to drift, and, by monitoring the process, we will be able to discover that change. The question then becomes how far the observations must drift before we decide that the process has changed. So, for every process, **control limits** need to be established to decide when to take action. When points fall outside of the control limits, this provides a signal that the process may have changed and some action is needed. We will discuss how to define the control limits and the various rules for deciding when action is needed in the rest of this chapter.

Using a control chart to monitor a process can be viewed as a graphical hypothesis test. The null hypothesis is that the process has not changed (both the mean and variance are constant). Various rules are used to decide when a signal has occurred (for example, an observation that falls more than 3σ from the mean is a common rule). When such a signal occurs, we reject the null hypothesis and conclude that a change has taken place. Of course, like all hypothesis tests, both Type I and Type II errors are always possible. In this context, a Type I error is a **false alarm**, requiring an unnecessary adjustment to the process. A Type II error is a failure to see a change in the process. The trade-off between the two types of errors and their relative costs in particular settings give rise to the many different rules for deciding when to reject the null hypothesis and declare a change in the process. Of course, rules that make it easier to reject the hypothesis will result in more false alarms and rules that make it harder will allow processes to drift farther (on average) before a signal is produced. Rules are often judged by how long they run, on average, without a false alarm when the process is in control. This is called the in-control **average run length** or **ARL**.

Control limits are based on the data themselves, and for that reason it is imperative that the process be in control before starting the monitoring process. Sometimes, however, quality concerns impose *external* limits on the process as well. For example, the diameters of the bolts must fall between certain limits or they just won't work. Limits such as these are **specification limits** because they are based on external specifications and not on how well the parts are actually produced. These upper and lower specification limits are abbreviated as USL and LSL, respectively. To understand how well the process is behaving compared to the specification limits, studies known as **process capability studies** are undertaken. Quality control practitioners use these studies to understand the relationships between the specification limits and the actual process parameters (mean and variance). Several different **process capability indices** measuring different aspects of the relationship are commonly used.

Process capability studies can be performed only when the process is in control. In other words, these studies involve only the common-cause variation and not special-cause variation. As long as the observations stay between the LSL and USL, the parts will meet specification. Ideally we would want the upper and lower specification limits to be as far from the process mean as is economically feasible. That width can be measured by $USL - LSL$. If the process can be centered at the desired mean, then by the 68–95–99.7 Rule, we know that observations farther than 3σ from the mean will be rare. The ratio $C_p = \frac{USL - LSL}{6\sigma}$ measures the ratio of the entire specification range (both sides of the mean) to 6 times the standard deviation of the actual process variation. A process with a C_p value of 1.0 would therefore just satisfy the 3σ on each side of the mean criteria and translates to about one observation in about 370 falling outside the specification limits, which is considered too often for most modern manufacturing and service industries. Usually it is recommended that C_p be at least 1.25, and sometimes as high as 2.0, but the actual choice depends on the economics of the situation and the type of industry. The larger this C_p value, the smaller the chance of an observation falling outside the specification limits. A large value of C_p indicates a process with a large potential to produce parts within the specification limits.

In any real process, no matter how stable, the mean will drift slightly even when the process is in control. Because C_p does not explicitly use the location of the mean it tends to overestimate the potential of the process when the mean is not centered and can be misleading. A measure known as C_{pk} is often used instead. When the process mean and standard deviation are known, C_{pk} is defined as:

$$C_{pk} = \min\left[\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right]$$

Using a period during which the process is in control to estimate the process parameters gives rise to the estimated value of C_{pk} .

$\hat{C}_{pk} = \min\left[\frac{USL - \hat{\mu}}{3\hat{\sigma}}, \frac{\hat{\mu} - LSL}{3\hat{\sigma}}\right]$ where the hats indicate that the parameters are estimated from the process data. Most studies recommend that the estimates of process capability be based on at least 50 observations. As with C_p the choice of how large a value of C_{pk} is acceptable or desired depends on the situation and the associated costs but values below 1.0 are rarely acceptable. Some industries (such as the automotive manufacturing industry) have specific guidelines that they publish. It is also important to remember that these indices rely heavily on the assumption that all observations are Normally distributed.

Fudge requires fairly strict adherence to a sequence of boiling sugar in milk until it reaches a certain consistency and then beating the mixture while it cools so that it acquires a smooth, creamy texture. A small candy company about 100 miles north of New York City ships fudge worldwide. If its fudge mix has a stable consistency, workers can control the weight of the fudge by simply timing how long they pour the warm fudge into the box prior to shipping. They would like the labeled 18 oz. box of fudge to contain no more than 18.5 oz. of fudge and no less than 17.9 oz. From the last 100 batches, they estimate the standard deviation of the weights to be 0.1 oz. with a mean of 18.1 oz.

MANAGER We need to get a better idea of whether our manufacturing process is under control. Please perform a process capability analysis on the fudge shop and comment on your findings.

ANALYST Our estimate of C_p is $C_p = \frac{USL - LSL}{6\sigma} = \frac{18.5 - 17.96}{6(0.1)} = 0.606 \approx 1.0$. Our estimate of C_{pk} is $C_{pk} = \min\left[\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right] = \min\left[\frac{18.5 - 18.13}{3(0.1)}, \frac{18.1 - 17.93}{3(0.1)}\right] = \min[0.403, 0.203] = 0.203$. The C_p value shows that if the weights are Normally distributed and the mean is centered, about 1 in 370 boxes will exceed the limits. This is a low C_p value, but it may be acceptable in this industry. However, the mean is not centered between the two limits and the C_{pk} value of 0.203 is too low. The candy company should work to center the mean and/or lower the standard deviation of the weights.

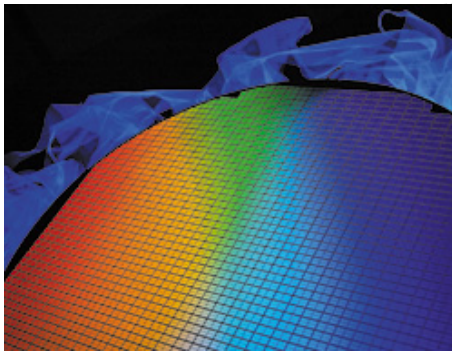
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22.2 Control Charts for Individual Observations (Run Charts)

The Sony Corporation of the 1950s used transistors and tubes for their electronic equipment, but nearly all their products today rely on computer chips. And almost all computer chips in use today are built on silicon wafers. Silicon is a natural semiconductor—it can be used both as a conductor of electricity and an insulator to prevent conduction. It is also relatively inexpensive and plentiful. The basic source of silicon is sand, which can be purified to produce chips that are 99.9999% pure silicon. Although there are many different kinds of chips (RAM, processors, etc.), they are all built from the basic silicon wafer. Making a wafer involves a number of steps, all of which must be carried out as consistently as possible to ensure the chip will be able to perform reliably, regardless of its final function. During the manufacturing process a variety of performance characteristics must be checked. These include physical measurements such as thickness, chemical properties involving purity, and electrical properties such as conductance. All of these have specifications depending on the type of chip being produced. Because billions of chips are manufactured worldwide every year, maintaining quality control on chip manufacturing is big business.



Rainer Plendl/123RF

Silicon wafers are produced in varying thicknesses, depending on their diameter. For photovoltaic use, a typical wafer is about 100–200 mm square with a thickness of 200–300 μm . The mean target thickness of the particular wafer whose production is studied here is 300 μm . One way to ensure quality is to keep the thickness as consistent as possible. We will use 250 past measurements of the process which has been judged to be in control to establish control limits. Here are the summary statistics and a histogram:

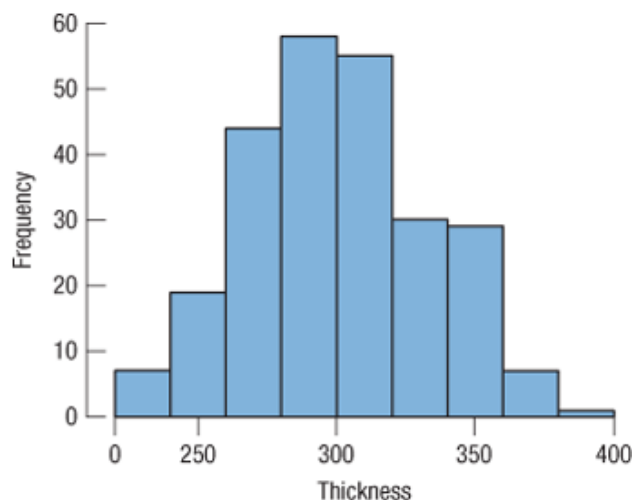


Figure 22.3

A histogram of the thickness shows a nearly Normal distribution centered at 300 μm .

maximum	392.423
quartile	325.067
median	298.521
quartile	277.030
minimum	221.838
Mean	301.111
Std Dev	32.990

Because the process has been judged to be in control, we can use the statistics from these data to develop control limits. We will base the mean at 300 μm , the desired thickness. The standard deviation of these measurements is 32.99. Using 33 μm as the standard deviation, (σ), the 68–95–99.7 Rule states that, as long as the process remains stable, only about 0.3%, or 3 of 1000, observations will fall outside of 3σ from the mean. Using 3σ the lower and upper control limits would be

$$\mu - 3\sigma = 300 - 99 = 201 \text{ and } \mu + 3\sigma = 300 + 99 = 399 \mu\text{m}.$$

Using these control limits, a control chart can be monitored to see whether the process stays in control. Here are the subsequent 50 thicknesses of the wafer manufacturing process:

Figure 22.4  shows a control chart for individual observations (sometimes called a **run chart** ), where a measurement is made on every product being produced. As we check each observation we are really performing a graphical hypothesis test, with the null hypothesis that the mean is 300 μm , and the (two-sided) alternative that it has changed to something else. The change may be abrupt, caused perhaps by a breakdown of a machine or the introduction of an impurity, in which case it is called a **level shift** . Or, the change might be gradual, in which case it is called a **trend** . We'll reject the null hypothesis if any point lies outside the 3σ control limits. The use of 3σ control limits as a standard is fairly widespread in the United States, while the United Kingdom and Europe tend to use other multiples of σ that depend on the specified probability of a Type I error, or false alarm signal. Using 3σ control limits will give rise to a false alarm rate of about 0.003 (using $1 - 0.997$ from the 68–95–99.7 Rule), or more precisely, 0.0027. That's the probability of any *single* observation giving rise to a false alarm. Even a process that is perfectly in control will have observations farther than 3σ from the mean, eventually (in fact, about 3 times in every 1000 observations). The average time between alarms for a process is the **average run length or ARL** . The average time between *false* alarms for a process in control is called the **in-control ARL** . We want as large an in-control ARL as possible, but at the same time, we'd like the ARL for a process that is out-of-control to be short. The in-control ARL can be calculated by taking the reciprocal of the false alarm probability. For the 3σ rule, the in-control ARL is:

$$ARL_0 = 1/p = 10.0027 = 370.37.$$

On average, we would expect to see a false alarm about every 370 observations for a process that is in control.

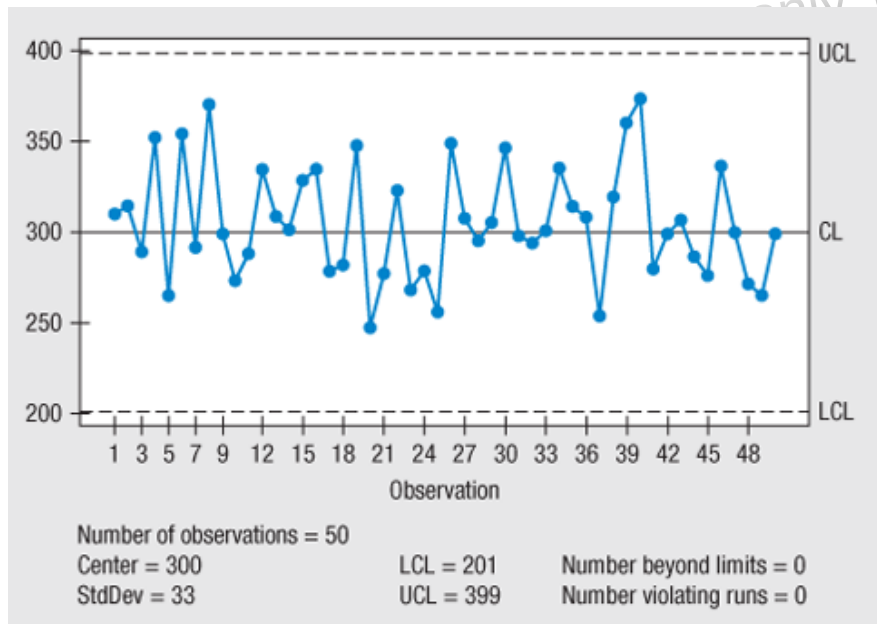


Figure 22.4

A control chart of individual observations shows no evidence that the process has slipped out of control. The 3σ lower (LCL) and upper (UCL) control limits are shown as dotted lines. The center line is denoted CL.

If the process mean shifts we'd like the control chart to show an alarm. If the chart shows the process staying in control, that's a Type II error. As in any hypothesis testing situation, the probability of the Type II error depends on how many observations have occurred since the process went out of control and how large the shift is (the effect size). Balancing Type I and Type II errors is an economic decision and depends on the control limits and the rule for deciding when a process has changed. The ability of any chart to detect shifts can be described by its **operating-characteristic (OC) curve** or equivalently by comparing the in-control and out-of-control ARLs. We describe shifts in mean in terms of standard deviations. If the process shifts only one standard deviation, the probability of noticing the shift on the next observation will be very small. If the shift were quite large, say, 5σ , we should be surprised if we didn't see it immediately. **Figure 22.5** shows an OC curve for the run chart just described:

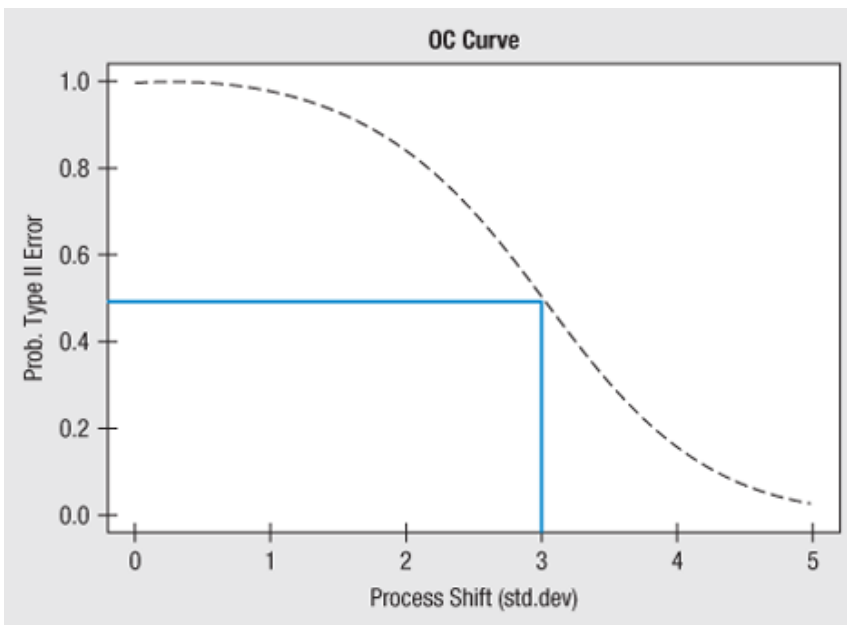


Figure 22.5

The operating-characteristic curve for a run chart. For a shift of 3σ the probability of not detecting it on the next observation is about 0.50.

Even though the probability of detecting a shift of 3σ is only about 0.5 on the *next* observation, the probability of a Type II error after two observations is about $0.5 \times 0.5 = 0.25$, and the probability of failing to detect the shift after 5 observations is $(0.5)^5 = 0.031$. More observations, of course, help guard against making errors.

In addition to the simple 3σ rule, there are many other rules commonly used in industry with different OC curves, and different ARLs. The Western Electric *Statistical Quality Control Handbook* (WECO, 1956) became a standard reference for quality control methods. It suggests several rules for deciding whether a process is out-of-control:

1. One point outside of the 3σ control limits on either side
2. Two out of three consecutive points beyond the 2σ “warning limits”
3. Four out of five consecutive points beyond 1σ from the mean
4. Eight (or seven) points in a row on the same side of the mean
5. Six points in a row increasing (or decreasing)
6. Fourteen points in a row alternatively increasing and decreasing

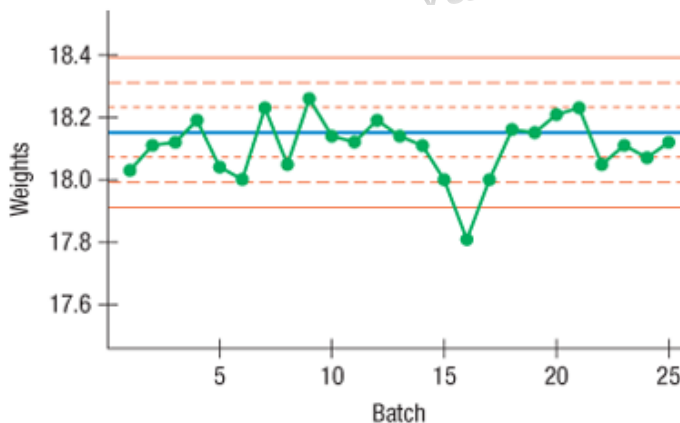
These rules are commonly used in practice. Some are available in commonly used software (notably Excel and Minitab), which implement several other rules as well. You may see eight or even ten rules used by software to detect a possible shift in the process. Deciding which combination of rules to use involves a trade-off between false alarms and failure to detect process changes. If the simple 3σ rule is the only one used, the in-control ARL before a false alarm, as we have seen, is about 370. If all 6 WECO rules are implemented, the ARL drops to about 92 observations between false alarms, but decreases the out-of-control ARL as well. Using more rules only decreases both ARLs even more. Each user has to decide whether the ability to detect shifts faster is worth the price of more frequent false alarms. It is also important

to note that these tests rely crucially on the assumption that the observations themselves are well-modeled by a Normal distribution. In the next section, we will plot *averages* of several observations and the Central Limit Theorem will help somewhat with this restrictive assumption.

In Practice 22.2 Runs charts

MANAGER After the report in (In Practice 22.1), we made some changes to the pouring process and think that the mean is now 18.15 oz. and the standard deviation is 0.08 oz. Using these parameter values, construct a runs chart for the following weights of recent batches and comment on whether the process is in control.

18.03	18.00	18.12	17.81	18.23
18.11	18.23	18.19	18.00	18.05
18.12	18.05	18.14	18.16	18.11
18.19	18.26	18.11	18.15	18.07
18.04	18.14	18.00	18.21	18.12



ANALYST It appears that the process is not yet in control. The weight of batch 16 is too low and, in fact, it is outside both the 3σ and the lower specification limit of 17.90.

22.3 Control Charts for Measurements: $\bar{x}$ and R Charts

Although the run chart of the last section is the easiest to implement and to understand, it is not usually practical to measure every item coming down a production line, or every phone call coming into a call center, especially if the testing is destructive. Nor are all observations Normally distributed. As an alternative, a sample is taken at periodic intervals and, typically, the *mean* of that sample is plotted. A chart of these sample means is called an **$\bar{x}$ chart** (pronounced “X bar chart” and often written as x-bar or x bar chart).

For detecting a shift in the mean, the $\bar{x}$ chart has several advantages over the run chart. A practical advantage is that it tests less frequently. Even more important, the averages from a sample of size n are more nearly Normal than individual observations, so that the basic assumption of the control chart that gives us the probabilities of a false alarm and other characteristics is more likely to be met. Because the sample sizes used in an $\bar{x}$ chart are usually small, however, it still relies somewhat on the underlying measurements being approximately Normal. Very skewed distributions will make the $\bar{x}$ chart inaccurate for detecting out-of-control signals.

When the standard deviation is assumed to be known (perhaps based on a large amount of past data), the implementation of the $\bar{x}$ chart is essentially the same as the individual control chart. Because a sample mean has a standard deviation of $\sigma/\sqrt{n}$ rather than σ , the 3σ control limits for the $\bar{x}$ chart become:

$$LCL = \mu - 3 \sigma / \sqrt{n}$$

$$UCL = \mu + 3 \sigma / \sqrt{n}$$

For the wafer data, if we continue to use $\mu=300$, and $\sigma=33$, and take a 5-item sample at regular intervals, the control limits become:

$$LLC = \mu - 3 \sigma / \sqrt{n} = 300 - 3(33/\sqrt{5}) = 255.7 \mu\text{m}$$

$$ULC = \mu + 3 \sigma / \sqrt{n} = 300 + 3(33/\sqrt{5}) = 344.3 \mu\text{m}$$

Figure 22.6 is an $\bar{x}$ chart for 25 samples of size 5 from the wafer production process:

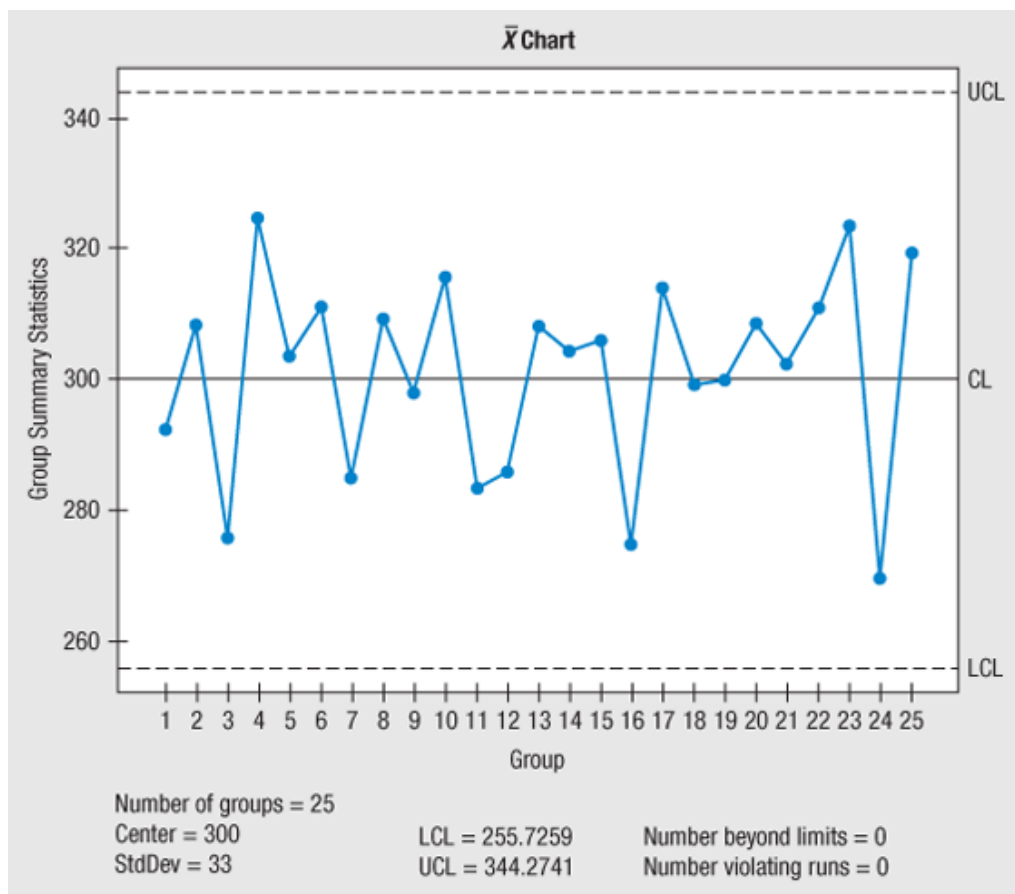


Figure 22.6

An $\bar{X}$ chart for 25 samples of size 5. The process appears to be in control because all sample means are within the control limits. This particular chart uses two of the Western Electric rules and reports *Number beyond limits* (rule #1) and *Number violating runs* (variant of rule #4—7 on same side of mean).

Up to now, we have assumed that the past data are numerous, so the mean and standard deviation of the process are known. In practice, we may not have this information, and we will have to estimate both μ and σ . These estimates should be based on as much data as possible—20 to 25 samples at a minimum—and, of course, the process must be in control. If we have k samples of size n , then we can use the average of the averages, called $\bar{\bar{X}}$ ($\bar{X}$ double bar), to get our estimate of μ :

$$\bar{\bar{X}} = \bar{X}_1 + \dots + \bar{X}_k$$

If no external center were desired, $\bar{\bar{X}}$ would be the center of our control chart.

To find the control limits, we still need an estimate of the standard deviation, σ . This is typically done by technology, or from the standard deviation of a large in-control sample, but can also be found by using the ranges of the samples rather than their standard deviations. Recall that the range of a sample is defined as the maximum minus the minimum:

$$R = \max - \min.$$

For Normally distributed data when no other reliable estimate of the standard deviation is available, we can use a well-known relationship between the range of a sample and its standard deviation. The mean of the

ratio $R\bar{\sigma}$ is a constant denoted d_2 , which depends on the sample size (and is given for various sample sizes in Table R in [Appendix B](#)). Using this constant, an estimate of σ is found from $\sigma^{\wedge} = R^{-}d_2$ where $R^{-} = R_1 + \dots + R_k$.

The limits of the control chart then become:

$$LCL = \bar{X} - 3\sigma^{\wedge}n = \bar{X} - 3R^{-}d_2n$$

$$UCL = \bar{X} + 3\sigma^{\wedge}n = \bar{X} + 3R^{-}d_2n$$

Suppose that instead of the 250 individual measurements we used previously to establish μ and σ , we had used the first half of these as a calibration set and then monitored the rest of the samples. In total we have 50 samples of size 5. From the first 25 samples of size 5 we compute their means and ranges and find:

$$\bar{X} = 295.27; R^{-} = 81.32.$$

To compute the control limits, we have $n=5$, and $d_2=2.326$, and so:

$$LCL = 295.27 - 3(81.322.3265) = 248.36$$

$$UCL = 295.27 + 3(81.322.3265) = 342.18$$

These are not very far from the control limits we found by assuming that the mean and standard deviation were known. But often control limits have to be adjusted as new information about the process performance becomes available. Quality control charting involves learning about a process as well as monitoring it. A more modern approach to process monitoring uses control charts to monitor the *inputs* to the process instead of just the measurements (outputs). In this way of thinking, if the critical inputs to the process are in control, the resulting outputs will be as well.

As we saw with run charts, the power for detecting a shift depends on the size of the process shift. For $\bar{X}$ charts it also depends on the sample size. To choose an appropriate sample size, quality control monitors examine the operating-characteristic curves such as the one shown in [Figure 22.7](#) based on the wafer data. Both the process shift and sample size can be used to find the probability of a Type II error for the next sample.

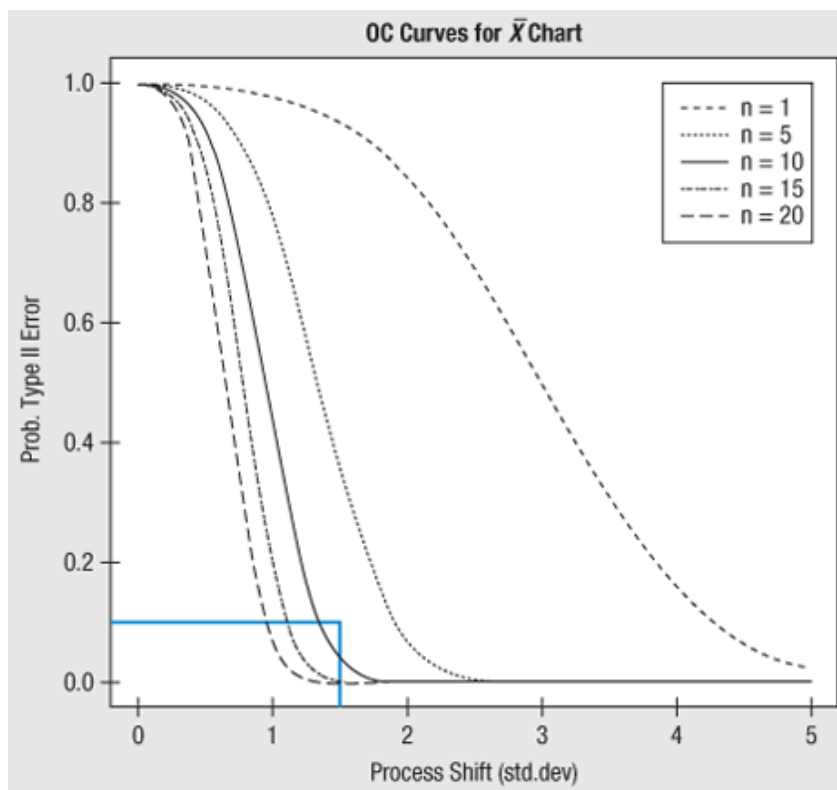


Figure 22.7

Operating-characteristic curves for the wafer data $\bar{X}$ chart. For any proposed value of the process shift (in standard deviations), operators can examine different sample sizes to determine a good sample size with a reasonable probability of a Type II error. For example, for a 1.50 shift, a sample size of more than 10 would be necessary to produce a probability of a Type II error below 0.10.

In general, we care about both the level of the process and consistency in variation. Although an $\bar{X}$ chart will detect increases in the standard deviation, for more information, the ranges themselves are plotted in what is known as an **R chart**. The procedure for setting up the R chart is very similar to the $\bar{X}$ chart. The only new element is finding the standard deviation of the range. Fortunately, for Normally distributed data, the relationship between σ and R is well known. There is a new parameter d_3 , that depends on the sample size as did d_2 . If we assume σ is known, we can find the standard deviation of the range directly by: $\sigma_R = d_3\sigma$. If we need to estimate σ , we can use $\sigma \approx R/d_2$ as before:

$$\sigma \approx R/d_2$$

We center the range chart at R , so the control limits:

$$LCL = R - 3\sigma_R$$

$$UCL = R + 3\sigma_R$$

become:

$$LCL = R - 3d_3 R/d_2$$

$$UCL = \bar{R} + 3d_3 \bar{R}/d_2$$

(If we are given both the mean and standard deviation from the process history and wish to establish limits for R , we can alternatively use $R = d_2\sigma$ as the center line.)

Using our 25 samples of size 5 with $\bar{R} = 81.32$, and finding d_3 for $n=5$ to be 0.864, we have:
 $\sigma^* R = d_3 \bar{R}/d_2 = 0.864 \cdot 81.322 / 0.326 = 30.21$. (Had we assumed $\sigma = 33$ we would have $\sigma R = 0.864(33) = 28.51$, not far from the value we obtained.) This gives us lower and upper control limits for the range of:

$$LCL = \bar{R} - 3d_3 \bar{R}/d_2 = 81.32 - 3(30.21) = -9.31 \quad UCL = \bar{R} + 3d_3 \bar{R}/d_2 = 81.32 + 3(30.21) = 171.95$$

Because a range can never be negative, we set the lower limit at 0.

Target Values

When using target or known values for the process mean and standard deviation the center lines and 3σ control limits are particularly easy to find.

For $\bar{X}$ charts:

center line: μ

UCL: $\mu + 3\sigma/\sqrt{n}$

LCL: $\mu - 3\sigma/\sqrt{n}$

For R charts:

center line: $d_2\sigma$

UCL: $d_2\sigma + 3d_3\sigma$

LCL: $d_2\sigma - 3d_3\sigma$

where d_2 and d_3 are found in

Table R for sample size n .

When not using external values for the process mean and standard deviation, these formulas can (and in industry usually are) simplified by noticing that we can collect the constants and rewrite the limits more simply as:

$$LCL = \bar{R} - 3d_3 \bar{R}/d_2 = \bar{R}(1 - 3d_3/d_2) = D_3 \bar{R} \quad UCL = \bar{R} + 3d_3 \bar{R}/d_2 = \bar{R}(1 + 3d_3/d_2) = D_4 \bar{R}$$

So now the upper and lower limits for the R^- chart are just multiples of R^- (and are found in Table R). For small sample sizes, $D3=0$, which automatically sets the lower range limit 0. (These simplifications should not be used if you want to base the limits on an *external* value of the process standard deviation or mean.)

For $n=5$, $D3=0$ and $D4=2.114$ so $LCL=0$ and $UCL=2.114(81.32)=171.91$, nearly the same (accounting for rounding) as we found before.

For R charts, the first four WECO rules are often used, although some adaptations for the fact that the chart is generally asymmetric exist as well. The chart below uses rules 1 and 4 (with seven) as it did for the $\bar{X}^-$ chart. Monitoring the next 25 samples, we see that the range stayed in control:

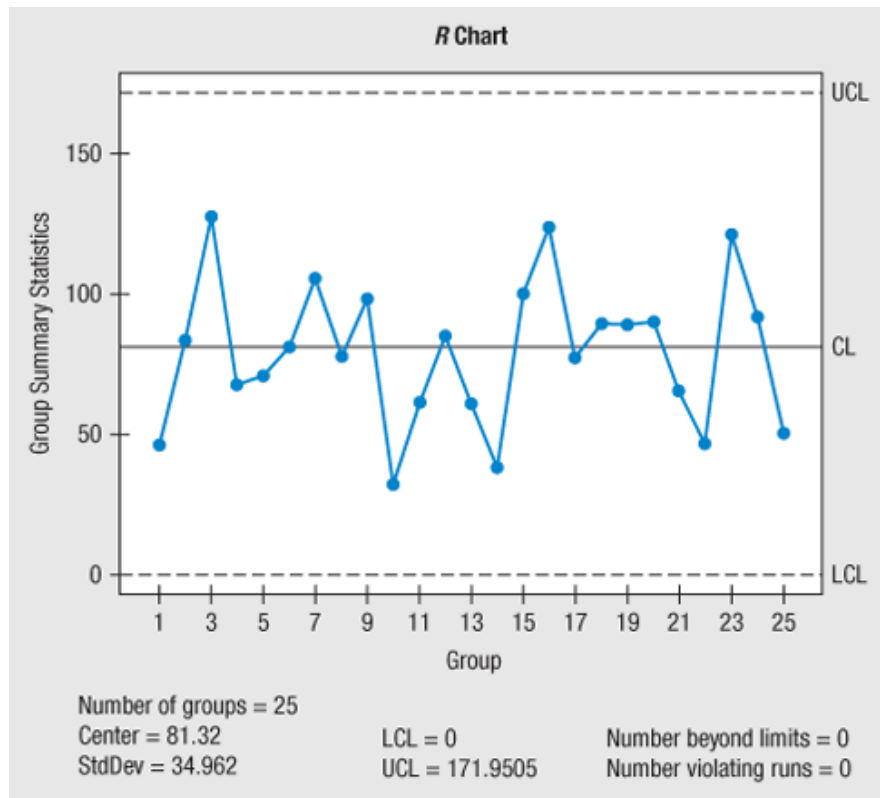


Figure 22.8

An R chart for 25 Samples of size 5. The process appears to be in control in terms of variation because all sample ranges are within the control limits.

An alternative to the R chart is the **S chart**, which uses the standard deviations of samples rather than their ranges. The most common use of $\bar{X}^-$ and S charts occurs when the sample sizes are moderately large (where the range loses statistical efficiency—around $n=10$ or 12) or when the sample size varies and the ranges of different samples are not comparable. The formulas for finding the control limits for both $\bar{X}^-$ and S are complicated and are usually left to technology to calculate. We refer the interested reader to any number of excellent texts on quality control.

In this section we have seen how to establish the most common control limits for $\bar{X}^-$ and R charts. $\bar{X}^-$ and R charts are the most commonly used charts for measuring quantitative values and are used together to monitor both changes in the mean and the spread of a process. However, it should be pointed out that the more rules one uses for detecting signals, the smaller the in-control ARL will be. So, using more of the

Western Electric rules or using $\bar{X}$ and R charts together will decrease the time to detect a true signal, but will increase the number of false alarms as well. Important alternatives to the $\bar{X}$ charts have been developed, among which the two most widely used are the cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) charts.

The CUSUM chart plots the cumulative sums of all the deviations of the values from the target mean. If the process stays in control, that sum should stay near 0 (although its variance will increase). If the process drifts, the sum will start to accumulate the differences (on one side of the target mean or the other). Because the variance of a sum increases even when the process is in control, the control limits are not lines equally spaced from the mean, but a V-shaped mask that moves as the number of observations increases. The EWMA chart, like the exponential smoothing method of [Chapter 20](#), weights recent observations more heavily so that past observations have decreasing importance as time rolls on. Both of these charts have been shown to provide advantages over $\bar{X}$ charts for many real-world situations.

Finally, it is important to point out that not all process changes are undesirable. In fact, in modern quality control, much emphasis is placed on reducing process variation. A shift indicating that the range (or standard deviation) has decreased would almost certainly be viewed as beneficial.

In Practice 22.3 $\bar{X}$ and R charts

MANAGER We've now made more changes to the process and wonder if we have been successful in getting the process under control. We still desire a mean of 18.1 oz. and a process standard deviation of 0.08 oz. Here are the average weights and ranges of 25 batches of size 5:

Batch	Mean	Range	Batch	Mean	Range
1	18.104	0.13	14	18.076	0.20
2	18.014	0.09	15	18.152	0.15
3	18.138	0.14	16	18.114	0.31
4	18.108	0.31	17	18.180	0.36
5	18.118	0.12	18	18.086	0.26
6	18.112	0.18	19	18.104	0.40
7	18.216	0.15	20	18.074	0.20
8	18.332	0.62	21	18.122	0.24
9	18.434	0.19	22	18.146	0.12
10	18.146	0.29	23	18.104	0.36
11	18.032	0.22	24	18.136	0.16

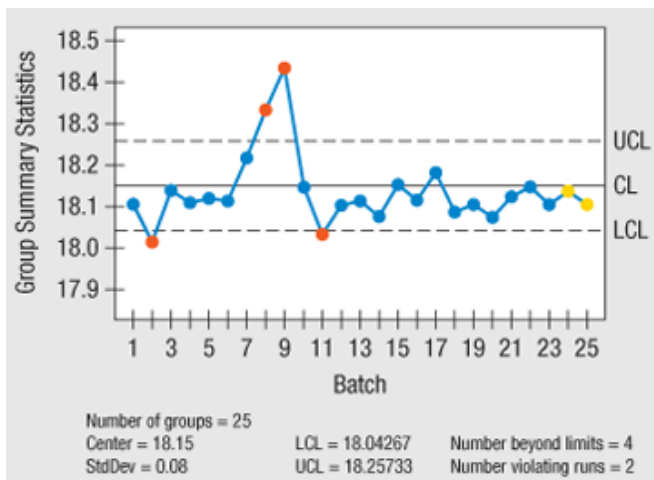
12	18.102	0.39	25	18.104	0.08
13	18.112	0.21			

Using $\bar{X}$ and R charts with the desired mean of 18.15 oz. and the desired standard deviation of 0.08 oz., does the process seem to be in control now? If not, when did the process seem to slip out of control?

ANALYST For the $\bar{X}$ chart, we use 18.15 as the center line and the desired process standard deviation of 0.08. The control limits are found at

$$\mu \pm 3\sigma = 18.15 \pm 3(0.08) = 18.15 \pm 0.24 = 17.91 \text{ and } 18.39$$

Here is the $\bar{X}$ chart of the 25 batches:

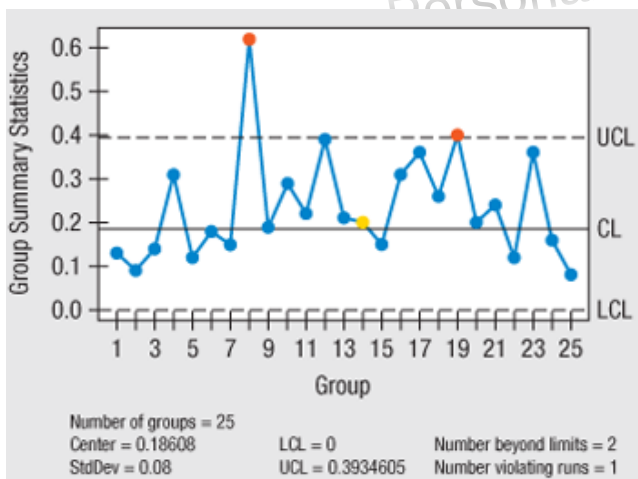


For the ranges, we use the desired process mean and standard deviation as well. So the center is

$$\text{center} = d_2\sigma = 2.326(0.08) = 0.186 \quad \text{LCL} = \text{center} - 3(d_3\sigma) = 0.186 - 3(0.864 \times 0.08) = -0.021 \Rightarrow 0$$

$$\text{UCL} = \text{center} + 3(d_3\sigma) = 0.186 + 3(0.864 \times 0.08) = 0.393$$

Here is the R chart:



The process is out of control both in mean and variation. Batches 2 and 11 were too low, and 8 and 9 were too high. Batches 8 and 19 had ranges too high and by Batch 14, there were seven ranges on the same side of the center line. The candy company clearly needs to study the process to bring it into control.

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22.4 Actions for Out-of-Control Processes

Once a process has been determined to be “out of control,” it does not necessarily mean that something is “wrong” with the process. It simply means that a signal has occurred indicating a possible change in the system. An action should be taken to understand the source of the special-cause variation. If the change is determined not to be beneficial, however, those in charge of the process must act quickly to resolve the problem. In the case of a detrimental change, an out-of-control signal may necessitate stopping production of the process until the cause has been determined and a correction put into place. This is the “Act” part of the Shewhart Cycle and a crucial step for process management.

For an established manufacturing process there may be an **out-of-control action plan (OCAP)** ⓘ in place based on past experience. An operator seeing an out-of-control signal would consult the OCAP and take the steps outlined in it and then continue monitoring the process to see if the process regained an in-control state.

If no such plan exists, as would be the case for a new process, an investigation of possible causes is undertaken. The full details of such an investigation are beyond the scope of this text, but the basic steps involve:

- Forming a team of all those involved in the process to discuss and enumerate the possible causes of the shift. A powerful tool in this effort is the **cause-and-effect diagram** ⓘ (sometimes called an Ishikawa or fishbone diagram) that helps organize the possible causes and helps prioritize them for further analysis. (See **Figure 22.9**. 📄)
- If no simple cause can be determined it may be necessary to commence a series of experiments using the most probable causes as the factors. There are efficient designs that can accommodate as many as a dozen or more possible factors in the initial investigation of possible causes.
- Once the most likely cause has been identified, and the optimal value for that factor has been determined, the process inputs are changed in an attempt to drive the process back into control.
- The monitoring process is restarted in the hope that the problem has been resolved, and the Shewhart cycle starts again.

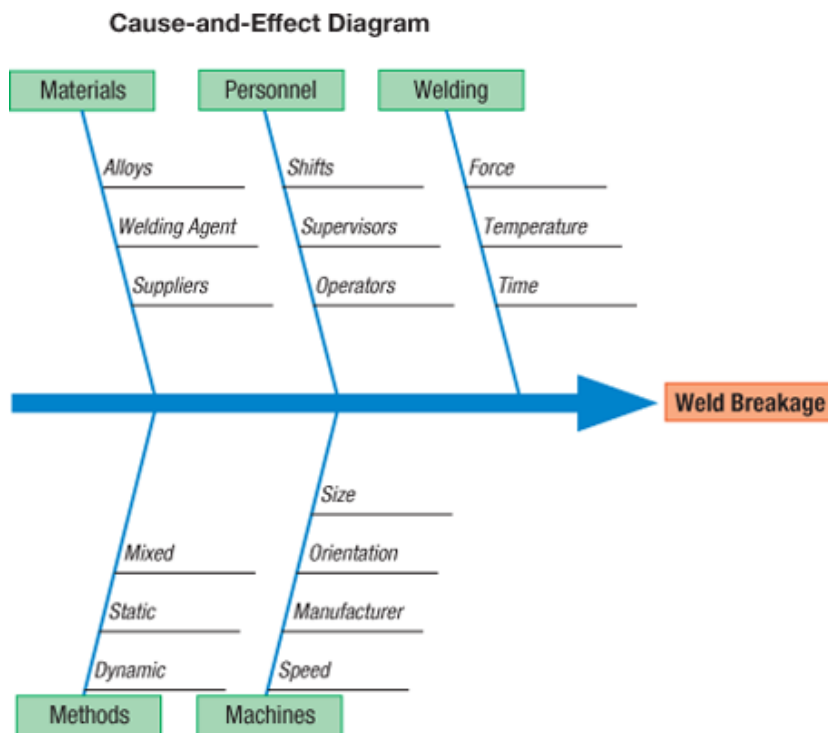


Figure 22.9

Cause-and-effect diagram for a production problem involving faulty welding between a detector and its base in a gas chromatograph. After a control chart showed the process was out of control, a team was assembled and together they listed 5 potential areas to investigate for process improvement: Materials, Personnel, Welding, Welding Methods, and the Machines involved. For each area, three to four potential factors were listed. From here, the team designed a series of experiments in the factors deemed most likely to affect weld breakage. The factors were manipulated and the resulting weld breakage was measured. Eventually it was determined that the alloy used by one of the suppliers had changed. When the company insisted that the supplier use the alloy that historically had been used for the weld, the problem disappeared.

Understanding and controlling processes is a large area of activity in both the manufacturing and service industries, involving the efforts of many people in the organization. The American Society for Quality (www.asq.org) provides a wealth of information on the subject.

In Practice 22.4 Actions for out-of-control processes

MANAGER We have now assembled a team of bakers, process engineers, and marketing staff. The team discusses possible factors influencing the weight and groups them into four main categories:

Raw materials (sugar, butter, milk, flavorings)

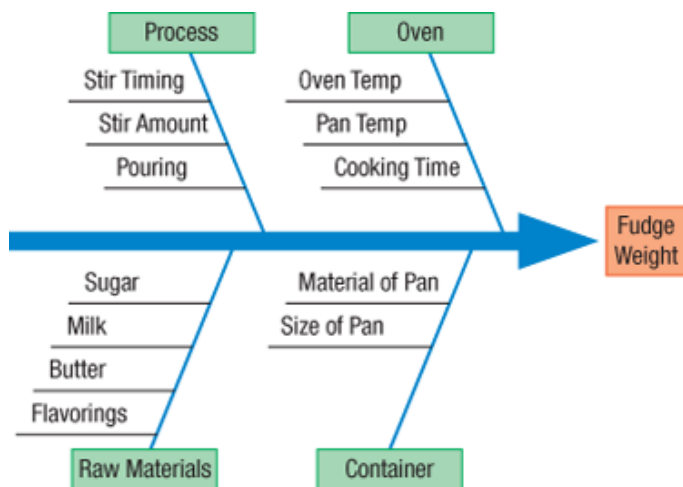
Oven (oven temperature, pan temperature, time)

Process (timing of stir, amount of stir, pouring of fudge)

Container (pan material, pan size)

Organize these possible factors into a fishbone (Ishikawa) diagram to help them design experiments using these factors.

ANALYST The diagram looks like this:



Guided Example KomTek Technologies



Skyhawk x/Shutterstock

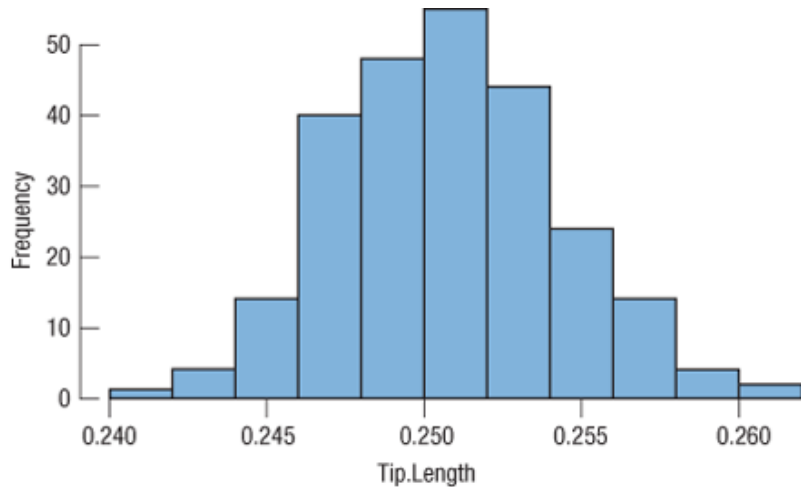
KomTek Technologies produces hip prosthetics in the United States with more than 60% of the U.S. market share. Founded in 1984, KomTek Technologies specializes in the production of nickel- and cobalt-based super alloys—specifically in the production of prosthetic devices. This manufacturing firm sells hip joints to five biomedical companies and these account for 30% to 40% of the firm's annual revenue. This firm uses a cobalt chromium alloy to forge the joints, which are heated in a furnace and then beaten or hammered into shape. Because prosthetic hips are costly to manufacture, the firm produces them only when a customer places an order. The average size of an order is typically between 200 and 600 pieces.²

²This example is based on 1998 case study written by J. Hunt, E. Landry, and J. Rao as part of the Babson College case series. The data and setting used in this example are based on the actual case study, but the data have been modified and the conclusions are fictitious.

Each part of the manufacturing process is monitored and controlled and the corporation has implemented a rigorous program to assist with quality control. Toward the end of the manufacturing process, dimples need to be hammered into each hip joint to enhance the fit. Occasionally, this hammering process causes the center line to be off-center. The tip length of this dimple is a crucial measurement to monitor.

A major customer that accounts for nearly 40% to 50% of the total hip joint sales at the firm recently placed an order for 1200 prosthetic hips—a larger than usual order. Following the manufacturing and shipment of these hips for this customer, the team at the firm responsible for quality control noticed that their overall cost for filling this order was high. The team members realized that the order was larger than usual, but they need to figure how and why the cost was so high. There was some concern by management that quality control monitoring may not have been in place for the latter part of this order. In particular, there was some suspicion that the last 230 or so hip joints had not been subjected to rigorous quality control.

We want to establish control limits for $\bar{X}$ and R charts for the *Tip Length* and investigate the recent production run to understand why the cost of recent orders has been high.

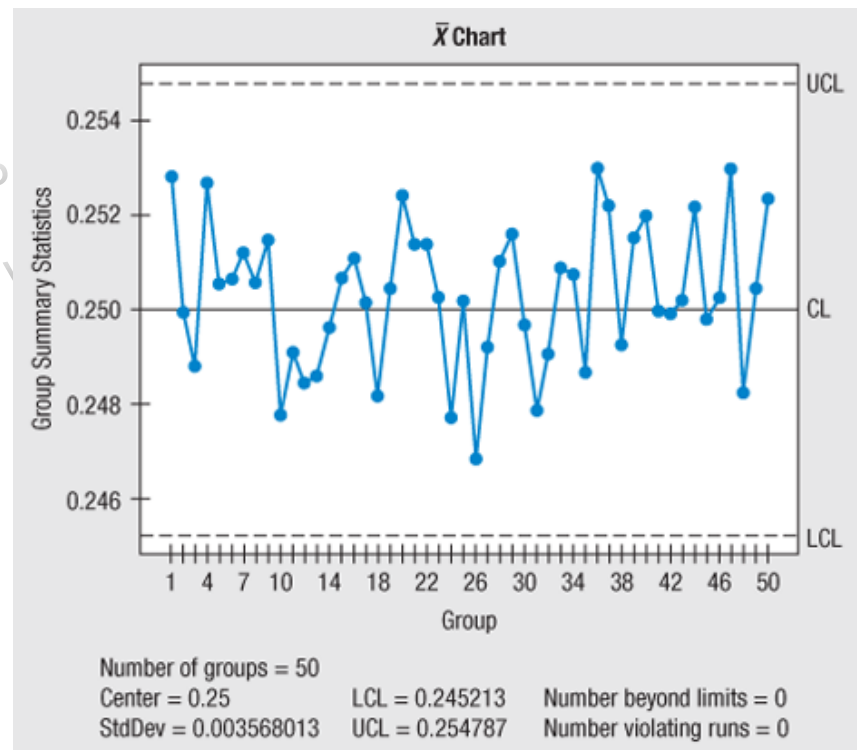
Define and state the objectives. Characterize the variables and their context.	We want to examine the variation in the Tip Length of the distal hip for the latter part recent large customer order to look for possible quality control issues. The tip length is 0.25 cm so we will use this as the center line. To start the monitoring process, we have data from 50 samples of size 5 from previous orders, when the process was judged to be in control (the calibration period), to use to establish our control limits.
Compute the limits using the specs provided by the company.	For the calibration period the overall mean is $\bar{X} = 0.2507$ inch. We will use 0.25, the specified length, as the center line. A histogram of these 250 observations shows a unimodal and symmetric distribution:  The average range for these 50 samples is $\bar{R} = 0.00847$ cm. Using the range to estimate sigma, we have:
Use software to create the	$\sigma^2 = \bar{R}^2 / d^2 = 0.00847^2 / 2.326 = 0.0036$ cm

$\bar{X}$ control chart.

Our initial control limits for $\bar{X}$ are therefore:

$$LCL = \mu - 3\sigma^n = 0.25 - 3(0.00365) = 0.2452 \text{ cm} \quad UCL = \mu + 3\sigma^n = 0.25 + 3(0.00365) = 0.2548$$

The $\bar{X}$ chart for the calibration data is shown here for completeness (although, of course we would not expect to see problems here because these are the data on which the limits are based):



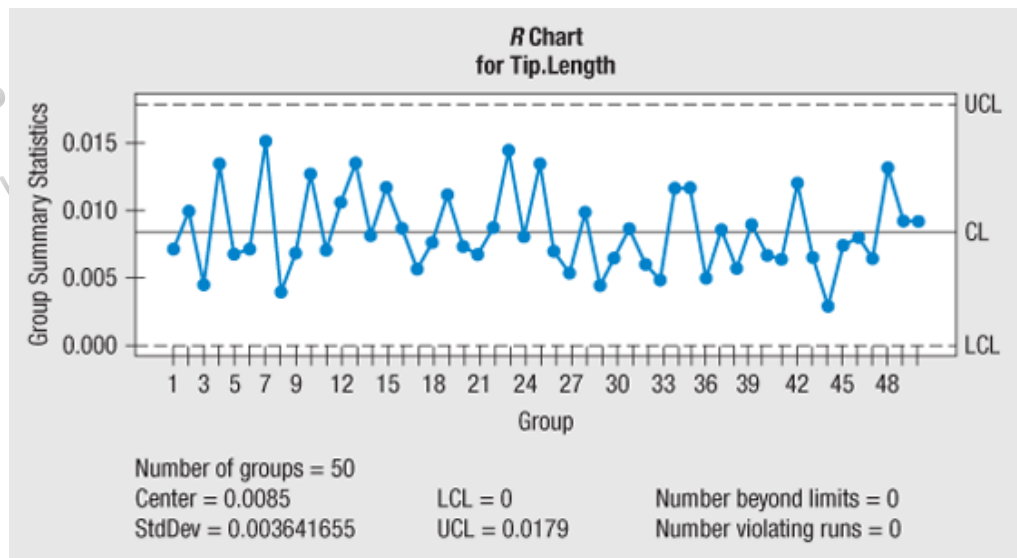
We use technology to create the R chart on the calibration data.

Similarly, we show the R chart for the calibration period.

For this period $R^- = 0.00847$. To establish control limits for the R chart we use

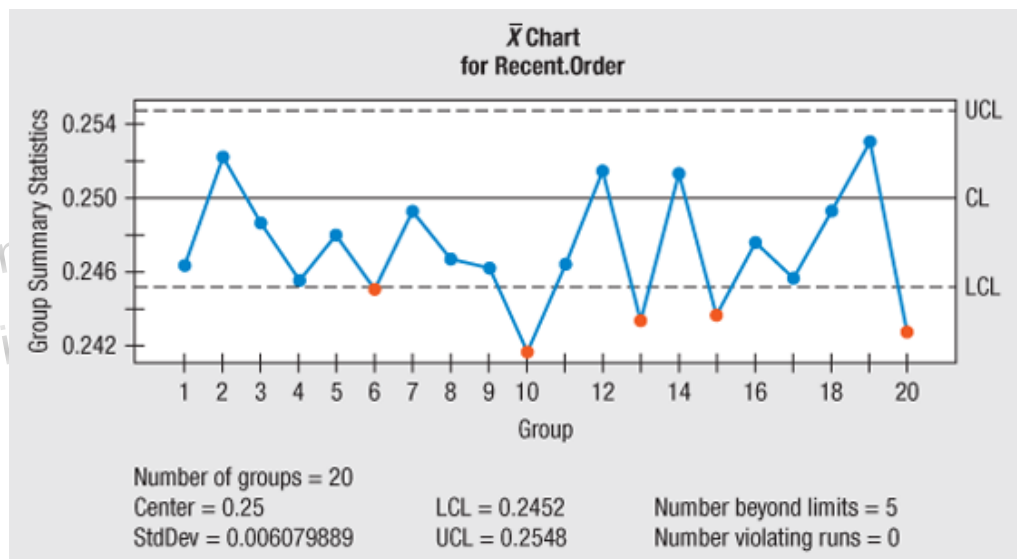
$$LCL = D3R^- = 0(0.00847) = 0 \quad UCL = D4R^- = 2.114(0.00847) = 0.0179$$

as the control limits.



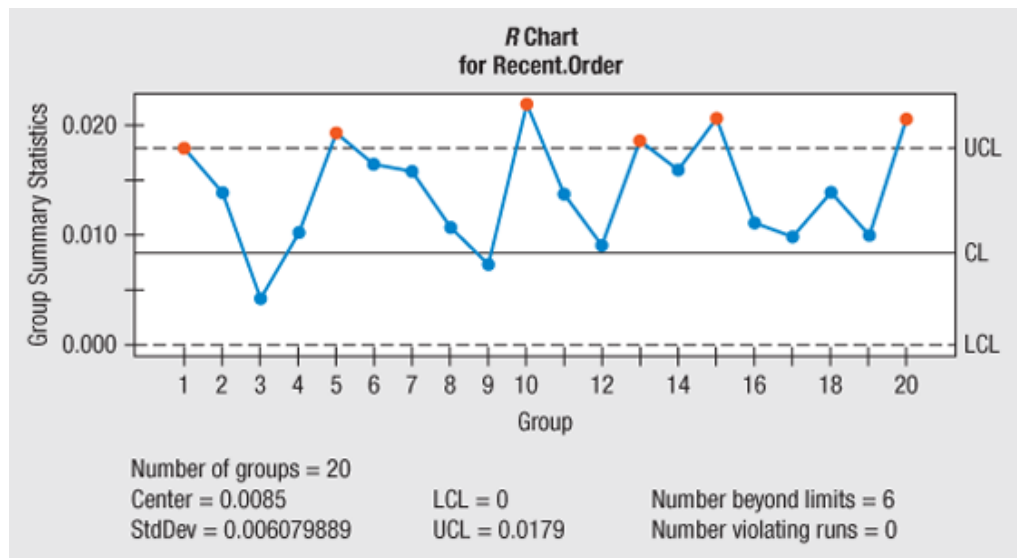
Examine the $\bar{X}$ and R charts for the recent order.

Using these limits, we now create $\bar{X}$ and R charts for 100 hip joints in the latter part the recent order, starting with unit 970 (20 samples of size 5). The $\bar{X}$ chart shows several problems:



There are 5 samples whose average tip length falls below the LCL. In addition, there were 9 samples in a row below the center line starting with sample 3. This should have been a signal that the process mean had shifted and some intervention should have taken place.

The R chart shows similar problems:



There are 6 samples whose range is too large (outside of the UCL). Starting with the sample, this should have been a sign that something had changed with the process.

Communicate and Present

State the conclusion in the context of the problem.

Memo

Re: Patterns of tip length

We investigated the variation in the length of the distal tip for this unusually large customer order. It is clear that quality control for the latter part of this order was lax. Several samples from units 970 to 1070 had average tip lengths that were too short. In addition, the volatility in the process also seems to have increased. The quality team notes that the length of the distal tip must be monitored using sampling during the process and the equipment should be checked, recalibrated, and/or changed after a violation of the limits in either the $\bar{X}$ or R charts.

Follow up

Following this incident, the team was assembled to try to diagnose the problem. None of the inputs to the machine that produces the part seemed to have changed. However, using a fishbone diagram, many possible causes of the problem were identified. After intensive discussion, four factors deemed most likely to affect tip length were selected for further study. An experiment testing these was designed and run. The analysis of the data showed that the tensile strength needed to be increased. A subsequent run of 5 tips showed that the problem had been resolved by this adjustment.

22.5 Control Charts for Attributes: p Charts and c Charts

We've seen several examples of quantitative measurements that are used to assess quality. For manufacturing processes these might include physical characteristics such as the thickness or diameter of a silicon wafer. In service industries, we might want to measure the length of time a customer has to wait to talk to a representative at a call center or how long it has been since they used one of our branches. Quantitative measurements are common, but we may want to monitor the quality of a process that has only categorical measurements such as color, or product type. The most common type of categorical measurements used in quality control are **dichotomous**—or yes/no—**variables**. Examples of these include whether a part is defective or nondefective or whether the customer has rated a phone call as satisfactory or not. In such cases, we can monitor the *proportion* of defective items in the sample. If it is determined that the proportion of defectives has increased, the special-cause variation will be investigated and the process will be adjusted to reduce variation. The control chart of proportions is called a **p chart**.

Recall that, if we assume the samples are independent, the standard deviation of a sample proportion $p^{\wedge}$ (writing q for $(1-p)$) is:

$$SD(p^{\wedge}) = \sqrt{pq/n}$$

If we know the desired proportion p , we can use this to establish 3σ control limits for the sample proportion:

$$LCL = p - 3\sqrt{pq/n}$$

$$UCL = p + 3\sqrt{pq/n}$$

In practice, however, we usually use the data from a period believed to be in control to estimate p and then use this value to monitor future data. As we did for $\bar{X}$ charts, we start by taking k samples of size n as our calibration data and base our control limits on the results. We'll call the average proportion of defective items from our k samples $\bar{p} = (p^{\wedge}_1 + \dots + p^{\wedge}_k)/k$. Recall that when we didn't know p , we used the sample proportion to find the standard error:

$$SE(p^{\wedge}) = \sqrt{p^{\wedge}q^{\wedge}/n}$$

We can use the same formula to estimate the standard deviation and find the control limits by using $\bar{p}$ in place of $p^{\wedge}$:

$$LCL = \bar{p} - 3\sqrt{\bar{p}\bar{q}/n}$$

$$UCL = \bar{p} + 3\sqrt{\bar{p}\bar{q}/n}$$

As with R charts, if the lower limit is negative, we set it to 0.

The usual point outside of the 3σ rule indicates a process that may be out of control. As with $\bar{X}$ charts there are a variety of alternative rules (WEICO). Minitab, for example, uses the following four:

1. One point outside of the 3σ lines
2. Nine points in a row outside of 1σ on the same side
3. Six increasing or decreasing points in a row
4. Fourteen points in a row that alternate up and down

For example, suppose that a wafer is defective if its film thickness is either too thin ($<250\text{ }\mu\text{m}$) or too thick ($>350\text{ }\mu\text{m}$). If we use 25 samples of size 50 as our calibration set we find $\bar{p}=0.1544$ and so

$$LCL=\bar{p}-3\sqrt{\bar{p}q/n}=0.1544-3\sqrt{0.1544\times0.8456/50}=0.001$$

$$UCL=\bar{p}+3\sqrt{\bar{p}q/n}=0.1544+3\sqrt{0.1544\times0.8456/50}=0.308$$

The p chart for the next 25 samples shows no evidence of a change in the proportion:

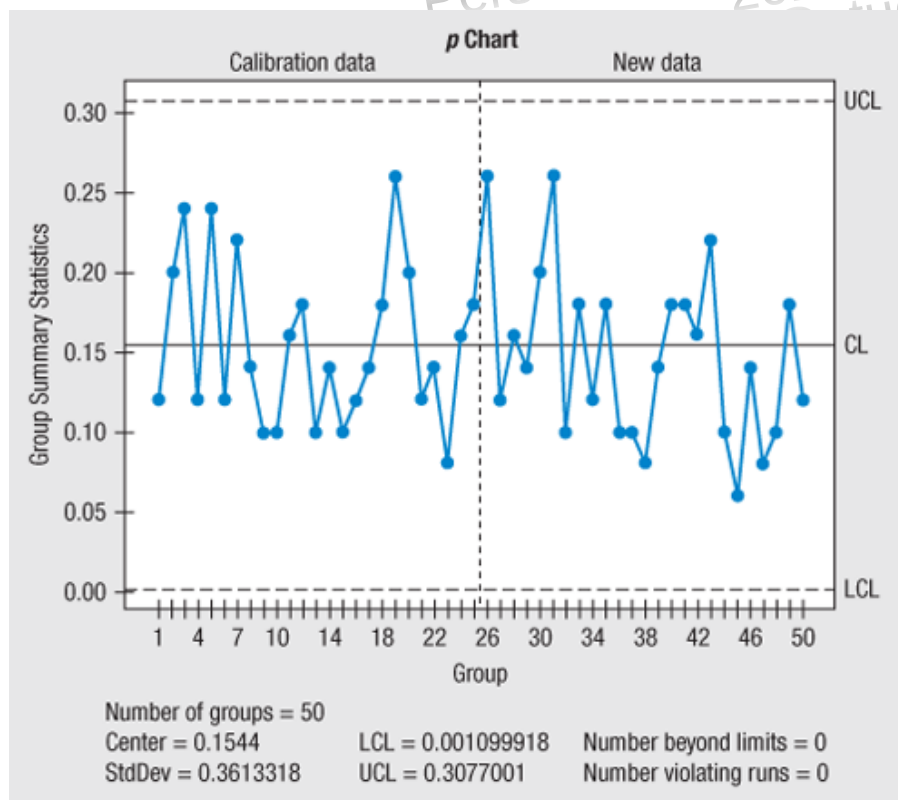


Figure 22.10

A p chart based on 25 samples of size 50 with an average proportion defective of 0.1544. The process appears to be in control in terms of variation because all sample proportions for the 25 samples after the initial calibration are within the control limits.

(Some computer programs have the ability to accommodate variable sample sizes for p charts, even though the control limits will vary with the sample size. If the sample sizes don't vary widely, it is also possible to use the average sample size and keep the control limits constant.)

Another variation on this type of monitoring focuses on the number of defective items in each sample rather than the proportion. This process is tracked in a **c chart**. The c chart should be used when the occurrence of a defective is *rare*. Then, the probabilities can be based on the Poisson model rather than the Binomial, which can lead to better ability to detect shifts. Because the standard deviation of a Poisson variable with mean μ is $\sqrt{\mu}$, we find the control limits easily. If the standard number of defects c is known we could simply use the 3σ control limits:

$$LCL=c-3\sqrt{c}$$

$$UCL=c+3\sqrt{c}$$

When no standard is given, we find the average number of defectives, $\bar{c}$, from k samples of size n and use that in the control limits centered at $\bar{c}$:

$$LCL=\bar{c}-3\sqrt{\bar{c}}$$

$$UCL=\bar{c}+3\sqrt{\bar{c}}$$

A more serious type of defect in wafer manufacturing is the failure of a die, the integrated circuit that eventually becomes a chip. If the number of failed dies per wafer is too great, the wafer is scrapped. If the number of scrapped wafers becomes too large, the process may need to be recalibrated or examined for other problems.

Suppose that for a period in which the process was in control, the average number of scrapped wafers was 1.44 in 1000. Then, in subsequent samples of size 500 we would expect 0.72 defect per sample. The control limits then become:

$$LCL=\bar{c}-3\sqrt{\bar{c}}=0.72+3(0.72)=1.826 \quad UCL=\bar{c}+3\sqrt{\bar{c}}=0.72+3(0.72)=3.266$$

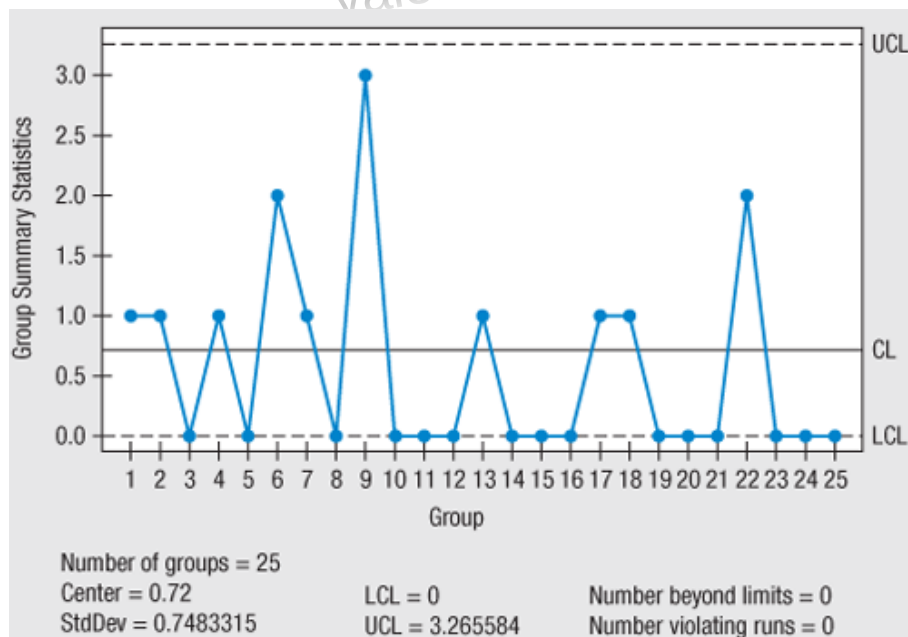


Figure 22.11

A c chart based on the same 25 samples of size 50 with an average number of defectives of 0.72. The process appears to be in control in terms of variation because all sample counts of defectives for the 25 samples after the initial calibration are within the control limits. Notice that the bottom control limit has been set to 0 because 3 standard deviations below 0.72 was negative.

In Practice 22.5 Control charts for attributes

MANAGER We have solicited customer feedback by surveys and phone interviews. One of the questions asks how satisfied customers were with the fudge on a scale from 1 to 5 with 1=Very Dissatisfied; 2=Dissatisfied; 3=Neither Satisfied nor Dissatisfied; 4=Satisfied; 5=Very Satisfied. They want 80% or more of their customers to be “Very Satisfied.” Here are the percentages saying “Very Satisfied” from the last 15 surveys of 100 people.

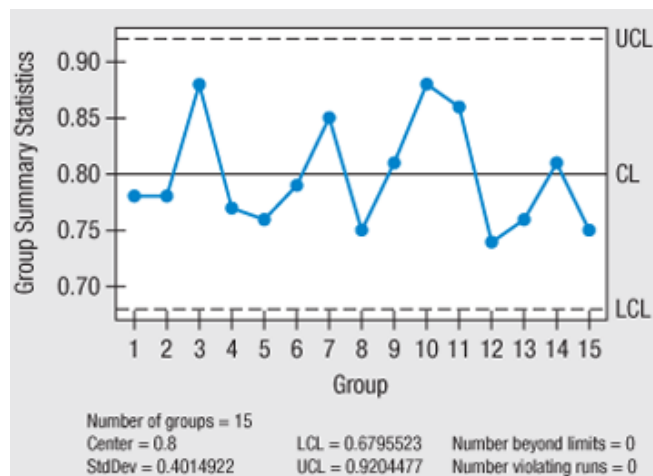
Number responding “5” out of 100: 78 78 88 77 76 79 85 75 81 88 86 74 76 81 75

Is the process “in control”?

ANALYST Using a p chart with center line $p=0.8$ the control lines are:

$$LCL=p - 3\sqrt{pqn}=0.8 - 3(.8)(.2)100=0.68 \quad UCL=p + 3\sqrt{pqn}=0.8 + 3(.8)(.2)100=0.92$$

From the p chart, it appears that the process is in control.



22.6 Philosophies of Quality Control

As U.S. industry saw its global market share slip in the 1970s and 1980s, and worldwide customers began to rely on Japanese and German products for high quality, a renaissance of interest in quality improvement sprang up all over the United States. During this time, many similar quality philosophies, acronyms, and gurus competed for the attention of top management. Most of them share three common ideas from statistical thinking as outlined by the Statistics Division of the American Society for Quality (ASQ):

- All work occurs in a system of interconnected processes,
- Variation exists in all processes, and
- Understanding and reducing variation are keys to success.³

³Glossary of Statistical Terms, Quality Press 1996.

Although the United States and Britain were the birthplace of modern quality control, the efforts of the quality movement in Japan caught the attention of U.S. industry in the decades after WWII. Deming is often credited for much of the success of Japan's manufacturing in the latter part of the twentieth century.

Deming ambitiously shared his ideas of concentrating on the customer and cutting costs by concentrating on quality in all aspects of the company in an effort to reduce waste and raise efficiency. Deming also suggested that the Japanese use market research—a new field in the United States and virtually unknown at the time in Japan—to help satisfy the needs of the customers. At the core of market research was the concept of random sampling to understand customers' desires and needs. Deming also conveyed the idea that managers need to take responsibility for quality control. He taught the Shewhart cycle and explained the importance of managers "acting" on the analytical information provided by the quality control tools. Deming also explained the importance of viewing the supplier as a partner and of building cooperative relationships, so that the supplier, producer, and customer all form a network. The teachings of Deming's philosophy can be summarized as **total quality management (TQM)** , although the term was not used until 1974 by one of the Deming Prize recipients.⁴ TQM extends the theory of quality control in that it encompasses the total organization, uses quality control methods, and focuses on the leadership provided by management to ensure long-term success, by focusing on customer satisfaction. It is a broad approach that seeks to improve all areas of the business to better satisfy the customer. The philosophy of TQM plays a central role in the Criteria for Performance Excellence, published in 1988, and the Baldrige National Quality Program (BNQP) that provides benchmarks for quality for organizations today.

⁴The American Society for Quality (ASQ) maintains that the term *TQM* was initially used by the U.S. Naval Air Systems Command in 1984 to describe the management approach to quality used in Japan because they did not like the term Total Quality Control.

W. Edwards Deming

W. Edwards Deming was decorated by the Emperor of Japan with the Second Order Medal of the Sacred Treasure in 1960 for his decade of contributions to Japanese production, and the

Japanese created the annual Deming Prize in his honor for recognition of achievements in producing a quality product. Dr. Deming was a member of the International Statistical Institute and was elected to the National Academy of Engineering.

Six Sigma® ⓘ is another business improvement approach that focuses more on the identification and elimination of defects or special-cause variation in business processes. Six Sigma was developed at Motorola during the 1980s but was picked up, expanded, and spread to other industries by General Electric and Allied Signal. Like other quality philosophies, the basis for the Six Sigma approach and philosophy was the early work of Shewhart, Deming, and others who furthered their efforts in the 1970s and 1980s.

All control charts are based on the idea that the process should be monitored to catch individual items or batches that are out of control. The core idea of Six Sigma is to reduce variation in the process to the point that inspection is no longer necessary. If the standard deviation can be made small enough so that the specification limits defining what it means for a part to be out of control are $4\frac{1}{2}$ standard deviations from the mean, then the probability of an out-of-control observation is only about 6 in 1,000,000. In real-life processes, the mean of the process can shift somewhat as well. To account for that the developers of Six Sigma added an allowance of a $1\frac{1}{2}$ standard deviation (sigma) shift. In this case, to achieve the 6 in 1,000,000 probability, the standard deviation has to be so small that 6 standard deviations are still within the control limit. This corresponds to a Cpk value of 2.0. At this point, it is no longer necessary (in theory) to monitor the process with control charts for inspection because the probability of being out of control is so small. Although this was the original idea of Six Sigma, it has become a much broader philosophy and approach to quality as practiced by large firms such as the General Electric Company. There is a hierarchy of experts (known as Black Belts) who, after being trained in the Six Sigma philosophy, act as internal quality consultants on a wide variety of quality issues.

Ethics in Action

Trax, one of the leading manufacturers of bicycles in the United States, is interested in expanding its line to include high-end road bikes. One of the features of high-end bikes, and one that avid cyclists pay top dollar for, is the use of super-light carbon fiber frames. Trax is currently in the process of selecting a supplier for these frames. Potential suppliers were asked to provide reports that included statistical process control (SPC) and capability data on their carbon fiber frame production processes.

Trax had specified the weight for these frames to be between 2 and 3 pounds with a target mean of 2.5 pounds. John Dickinson, Vice President of Operations, was in charge of summarizing the information contained in these reports to present at an upcoming senior management meeting at which a final decision on a supplier would be made.

As he reviewed the reports, he noticed that one supplier, DBS, could provide the frames at a much lower cost than its competitors. Eager to save the company money, he carefully considered this supplier's SPC and process capability data. John was pleased with their $\bar{X}$ and R charts for weight that indicated the process was stable (in statistical control). He was also pleased to be able to verify from these charts that their reported process standard deviation is only 0.1 pound and that the C_p index of 1.67 indicates that they would be able to easily meet Trax's weight requirement. While he did notice that the process mean was a bit off target (at 2.8 rather than 2.5 pounds), he decided that the significant cost savings that Trax would realize by choosing this supplier outweighed any potential negative consequences of a shifted process mean. John decided that he would present only cost data and the C_p index for the suppliers under consideration, and conclude his presentation at the senior management meeting with a recommendation that Trax choose DBS as its supplier of carbon frames. He believed that the team would be quite impressed with his cost-saving recommendation.

- **Identify the ethical dilemma in this scenario.**
- **What are the undesirable consequences?**
- **Propose an ethical solution that considers the welfare of all stakeholders.**

Chapter 22 From Learning to Earning

Learning Objectives

Understand the principles of quality control.

- A process is in control if the aspects being followed stay within the control limits established for them.
- When a process drifts out of control, it is important to recognize the fact so that adjustments can be made promptly. But we hope to avoid making too many false alarms, so a balance must be found.

Use run charts to track individual observations.

- A level shift flags a sudden change. A trend is a more gradual change.
- The ability of a chart to detect shifts is described by its operating-characteristic (OC) curve.
- The Western Electric Handbook specified several rules for deciding when a process is out of control.

Use $\bar{X}$, R , and S charts to track a process by plotting the means, and ranges or standard deviations of small samples drawn from the process.

- The control limits are often based on estimated standard deviations and means.
- The S chart, which uses the standard deviations of the samples rather than their ranges is more appropriate than the R chart used when the samples are moderately large.

Understand the basic steps in creating an out-of-control action plan (OCAP).

- A cause-and-effect diagram helps organize possible causes and prioritize them for further analysis.
- It may be necessary to perform experiments to determine the cause of the problem.
- Once a cause is identified, process inputs can be adjusted to drive the process back into control.
- The monitoring process can then be restarted.

Use p charts and c charts to track processes that have categorical measurements.

- A p chart tracks proportions using control limits based on the standard deviation of a proportion.
- A c chart tracks the number of defective items in a process.

Understand the basic philosophies of quality control, such as Total Quality Management (TQM) and Six Sigma®, and how they are applied to improve business performance and quality.

Terms

Average run length (ARL)

The in-control ARL is the average time between false alarms, calculated by taking the reciprocal of the false alarm probability. The out-of-control ARL is the average number of runs until a signal is detected. It depends on the state of the process while out of control.

c chart

A control chart that displays the counts, or number, of occurrences of defectives (or nondefectives if rare) in samples taken from a process over time.

Cp

A process capability index that measures the ratio of the specification limit range to 6 times the standard deviation of the process without taking into consideration possible drift of the process:

$$Cp = \frac{USL - LSL}{6\sigma}$$

Cpk

A process capability index that measures what the process is capable of producing, estimated by:

$$C^{pk} = \min \left[\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma} \right]$$

Common-cause variation

Variation characterized by apparent random fluctuations around an average level within specified limits called control limits.

Control chart or Shewhart chart

A graph that displays variation by plotting individual measurements or sample statistics taken from a process over time, sometimes referred to as a Shewhart chart.

Control limits

Horizontal lines drawn on a control chart. Various rules are used to determine when a process is out of control depending on the specific control chart.

Dichotomous variable

A categorical variable that has only two possible outcomes such as success or failure. Also called a yes/no variable.

False alarm

A Type I error indicating that the process is out of control, when in actuality, it was due only to common-cause variation.

Level shift

A sudden and sustained shift in the mean of the measurements being monitored.

Operating-characteristic (OC) curve

A chart that shows the probability of failing to see a process shift (a Type II error) plotted against the size of the shift (in standard deviation units).

Out of control

The presence of special-cause variation in a process.

Out-of-control Action Plan (OCAP)

A set of instructions to follow for well-established processes indicating what action to take following an out-of-control signal.

p chart

A control chart that displays the proportion of defectives (or nondefectives) in samples taken from a process over time.

Process Capability Study

A study that compares the variability of the process to the specification limits imposed on the process by external concerns. Two of the most common process capability indices are Cp and Cpk.

R chart

A control chart that plots the ranges of samples taken from a process over time.

Run chart

A control chart that displays individual measurements from a process taken over time.

S chart

A control chart that plots the standard deviations of samples drawn from a process. It may be preferred to the *R* chart when the samples are relatively large (10 or more).

Six Sigma[®]

A quality control philosophy based on reducing variation to the point where inspection sampling is no longer necessary. The philosophy's name comes from the fact that if specification limits (plus possible drift) are 6 standard deviations from the control center line, the chances of an out-of-control part are negligible.

Special-cause variation

Causes of variation that are not intrinsic to the process and thus whose presence is important to detect.

Specification limits

Limits above (and/or below) which a measurement should not lie, imposed by external considerations.

Statistical process control (SPC)

The examination of variation in a process over time to identify sources of variation.

Total quality management

Extends the theory of quality control to include the total organization and the leadership of management.

Trend

The gradual shift of a process mean.

$\bar{X}$ or x-bar chart

Control chart that displays the averages of samples taken from a process over time.

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Tech Support Quality Control Charts

EXCEL

Excel does not offer quality control charts. A number of third-party add-ins and templates are available.

XLSTAT

To implement control charts for desired bounds:

- From the XLStat tab, choose the **XLStat-SPC** toolbar.
- Select either **Subgroup charts** (for $\bar{x}$ -bar and r charts) or **Attribute charts** (for p and c charts).
- Select the desired chart from the **Mode** tab in the dialog box.
- Under the General tab, type the data range into the **Data** field.

If your data have sampled values in rows for each sample, choose the **Data Format Columns**.

- In the **Options** tab, you can type in your UCL and LCL directly, but if you leave these fields blank, XLStat will compute these for you.
- If you have a specific value for the mean, type it in. Under the **Estimation** tab, choose **R bar** as the **method for sigma**.

JMP

From the **Analyze** menu select the **Quality and Process** submenu. There you will find a variety of control charts and quality control analysis methods in the **Control Chart Builder**.

MINITAB

From the **Stat** menu, select the **Control Charts** submenu. There you will find an additional level of submenus offering Variables Charts for Subgroups, Variables Charts for Individuals, Attributes charts, and Time Weighted charts. Standard control chart types are found within these submenus.

SPSS

From the **Analyze** menu, select the **Quality Control** submenu. Selecting **Control Charts** from that submenu brings up a dialog box from which you can select the chart type and specify other details.

STATCRUNCH

From the **Stat** tab, select the **Control Charts** submenu. You will find a variety of control charts and quality control methods.

R

There are several packages that can be used in R to produce quality control charts. Using package QCC, use a command like: `q <- qcc([dataset name], type="R", nsigmas=3)` to produce an R chart. Use a command such as: `process.capability(q, spec.limits=c([lower limit], [upper limit]))` to produce an X bar chart.

Brief Case

Laptop Touchpad Quality



Stefan Kiefer/imageBROKER/Alamy Stock Photo

Consumers always seem to want thinner and lighter electronic products, and computer laptops are no exception. One of the challenges of producing extremely thin and light laptops is the manufacturing of the touch pads. In particular, touch pads are difficult to align. A common complaint is that one corner is higher or lower than another, resulting in what is known as “tilting.” Tilting makes navigation difficult, so touch pad manufacturers have strict limits on the amount of tilting that they will allow in a pad.

A company producing touch pads will want to ensure that the pads are flat to within a certain acceptable tolerance. One possible measure is the total deviation from flatness as measured by the maximum difference in height between any two corners (in mm). In the data file **QC Control** you will find this flatness measure for 250 touch screens produced during a period that was judged to be in control.

Using the mean and standard deviation from this control period, examine the next 150 samples of 5 pads (in the data file **QC Production**). Using various quality control rules and appropriate graphs, do you think the process is still in control? Explain.

Instead of samples of size 5 suppose they had used a run chart on the individual pads. Would your answer change? Explain.

Suppose the engineers establish 14 mm as the maximum flatness deviation they will tolerate and want to use that as an upper specification limit. Does your answer change now? Explain.

A qualitative measure is clarity of the pad. Batches of 100 pads are produced and defects are counted where defect is defined as a pad that does not pass the clarity test. From a period that was deemed to be in control, the mean number of defects per 100 was 0.5. Using this mean, determine whether the process stayed in control for the next 50 batches (**QC Clarity**).

Chapter 22 Exercises

Section 22.1

1. A producer of beverage containers wants to ensure that a liquid at 90°C will lose no more than 4°C after 30 minutes. Containers are selected at random and subjected to testing. Historical data shows the standard deviation to be 0.2°C. The quality control team has set 3.5 and 4.5°C as the specification limits. Here are the data from the last 12 containers tested:

Container #	Temperature Loss (°C)	Container #	Temperature Loss (°C)
1	3.89	7	4.22
2	3.71	8	4.02
3	4.14	9	4.48
4	4.12	10	3.93
5	3.74	11	3.87
6	3.99	12	3.94

- a. Make a control chart of these data using the specification limits given.
b. Does the process seem to be in control?
c. What is the value of C_p for the process?
d. Given this value of C_p , what recommendations might you make to the quality control team?
2. A computer screen manufacturing process must produce screens of uniform size. In particular, for a new tablet, the screen should be 10.1 inches long. The engineers have set 10.16 and 10.04 as the upper and lower specifications on screen length. If the actual process standard deviation is 0.01 inch,
- a. What is the value of C_p for the process?
b. What might you recommend to the engineers given this value of C_p ?