Supply and Operations Management Collection

M. Johnny Rungtusanatham, *Editor*

Statistical Process Control for Managers

Victor E. Sower

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Abstract

Davis Balestracci recently wrote, "When I look at training materials or books (on statistical process control), their tendency is to bog down heavily in the mechanics of construction without offering a clue about interpretation."[1] If you have been frustrated by very technical statistical process control (SPC) training materials, then this is the book for you. This book focuses on how SPC works and why managers should consider using it in their operations rather than on how to calculate limits for control charts. It provides the reader with a conceptual understanding of SPC so that appropriate decisions can be made about the benefits of incorporating SPC into the process management and quality improvement processes. An extensive list of references is provided for those readers who wish to dig deeper into the technical details of SPC.

SPC is designed to facilitate making better, more informed decisions about processes. SPC can indicate whether a process should be adjusted or left alone. It can also indicate when a process needs improvement to meet requirements, often can indicate a starting point for improvement projects, and can also provide documentation of the results of process improvement activities.

SPC as we know it was developed by Walter Shewhart in the 1920s and 1930s. Properly employed, SPC can be a significant factor in the control and minimization of variation in the manufacture of products and the delivery of services. It can greatly reduce the time it takes to recognize problems and provide information useful in the identification of root causes of those problems. SPC is also useful in demonstrating that a process is capable of consistently delivering what the customer wants. For this reason, some organizations require their suppliers to use SPC in order to become preferred suppliers. SPC also can provide conclusive evidence for the effectiveness of continuous process improvement programs.

The concept of SPC is relatively simple and with today's modern software packages, the mechanics of using SPC are simple. But that simplicity can lead to problems. With modern software packages anyone can create control charts from data without understanding the key concepts that make those control charts useful, how to interpret the charts they create, or how to use the information the charts provide to improve processes.

The purpose of this book is to provide the necessary understanding to effectively utilize SPC to improve quality and consistency of both products and services.

Because today there is little need to make the necessary calculations by hand, the book focuses little attention on manual calculations. Rather, the book primarily utilizes Minitab and NWA Quality Analyst, two of the most popular statistical analysis software packages on the market. Links are provided to the home pages of these software packages where trial versions may be downloaded for evaluation and trial use.

Unlike statistics and statistical quality control textbooks and manuals, this book does not address the tedious topic of how to construct control charts by hand. Instead, it covers the basic statistical concepts behind control charts to provide basic understanding of what is going on and then discusses the basics of using software products to create the charts.

The book also addresses the question of why SPC should be considered for use, the process of implementing SPC, how to incorporate SPC into problem identification, problem solving, and the management and improvement of processes, products, and services. Examples from my 25 plus years of experience with SPC are included to illustrate main points in the book. References are also included for readers who wish to delve more deeply into the technical aspects of SPC.

Keywords

control chart, out of control, process capability, SPC, SPC implementation, SPC use, statistical process control, variation

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Abbreviations and Acronyms

ASQ	American Society for Quality
ASQC	American Society for Quality Control
c-chart	count chart
CL	center line
CQI	continuous quality improvement
DPMO	defectives per million opportunities
EPA	Environmental Protection Agency
EWMA	exponentially weighted moving average
F	Fahrenheit
HVAC	heating, ventilation, and air conditioning
I-chart	individuals control chart
ISM	Institute for Supply Management
JIT	just in time
KPI	key performance indicator
KQC	key quality characteristic
LCL	lower control limit
LIL	lower inner limit
LSL	lower specification limit
LWL	lower warning limit
MCL	maximum concentration level
MR chart	moving range control chart
NIST	National Institute of Standards and Technology
np-chart	number defective control chart
NWA QA	Northwest Analytical Quality Analyst
OM	operations management
p-chart	proportion defective control chart
P&L	profit and loss
PMI	Purchasing Managers Index
ppm	parts per million
ppmd	parts per million defective
psi	pounds per square inch

psig	pounds per square inch gauge
R-chart	range control chart
R&R	repeatability and reproducibility
ROI	return on investment
s-chart	standard deviation control chart
SCM	supply chain management
S&OP	sales and operations planning
SOP	standard operating procedure
SPC	statistical process control
StDev	standard deviation
T	target value of the specification
u-chart	defectives per unit chart
UCL	upper control limit
UIL	upper inner limit
USL	upper specification limit
UV	ultraviolet
UWL	upper warning limit

Testimonial

This book is a must read for those who want to better understand and improve their processes and it should have great value as a desk reference. The case studies very well illustrate how SPC is used in a variety of industries. Sower shows that "data are all around us"— we just need to be able to recognize the data and know how to apply it to statistical process control (SPC). The discussion of uncertainty, precision, and accuracy is well done. Not only does the book describe the SPC methodology, but it also makes a good case for empowerment down to the lowest level. It reminds us that empowerment really enhances team building and hopefully results in a better product.

—Richard Bozeman, Jr.
Author and Inventor
Retired Chief of the Propulsion and
Power Division Test Facilities
NASA

Preface

Advertising mogul David Ogilvy complained that the advertising business tries to impress by using pretentious jargon. I have heard some business people speak in the same way about statistics and in particular statistical process control (SPC). They say that when they ask an expert about SPC, they receive a response filled with statistical jargon, equations, and Greek letters. Admittedly, to be an expert in SPC, one needs to understand the statistical jargon, equations, and Greek letters, and every organization using SPC needs at least one such expert. But not everyone in the organization needs to be an expert in order to take advantage of the remarkable benefits that can be attained from implementing SPC.

This book is designed to introduce SPC to working professionals who have little or no expertise in statistics. It uses very little statistical jargon, few equations, and just the bare minimum of Greek letters. The chapters contain many illustrations and examples to help the reader better conceptualize the material.

The objective of the book is to provide readers with a conceptual knowledge of SPC and what it can do for organizations that implement it. References are provided for readers who wish to acquire more depth in the subject. But readers whose only acquaintance with SPC is just having read this book will be better able to converse with the experts to understand what the experts recommend and to take appropriate actions based on those recommendations.

Appendix A consists of a bare bones introduction to statistical concepts and terminology. Those with no background in statistics may wish to read Appendix A before reading Chapter 3. The book incorporates the use of SPC software to crunch the numbers instead of emphasizing how to make the calculations by hand. It is important that users have knowledge of what the software is doing, so the reader is advised not to rely on software applications without having a firm grasp of the underlying statistics when using SPC. Appendix B contains information about the SPC software used in this book.

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CHAPTER 1

The Value SPC Can Add to Quality, Operations, Supply Chain Management, and Continuous Improvement Programs

We don't like volatility. Nobody likes volatility.

—Lionel Guerdoux Managing Partner,
Capricorn Venture Partners

Uncertainty is something organizations struggle to deal with. A few examples of how organizations cope with uncertainty include pro formas, which are prepared for a variety of contingencies; forecasts that are created with confidence intervals to assess the magnitude of uncertainties; production planning, which often involves an attempt to predict the range of unpredictable possibilities that render the plan obsolete on a nearly daily basis; and order quantities that include safety stock.

Statistical process control (SPC) is defined by the American Society for Quality as "the application of statistical techniques to control a process."[1] Properly employed, SPC can be a significant factor in the control and minimization of variation and the resulting uncertainty in the manufacture of products and the delivery of services. It can greatly reduce the time it takes to recognize problems and provide useful information for the identification of root causes of those problems. The result often is better quality and lower costs.

SPC is also useful in demonstrating that a process is capable of consistently delivering what the customer wants. For this reason, some

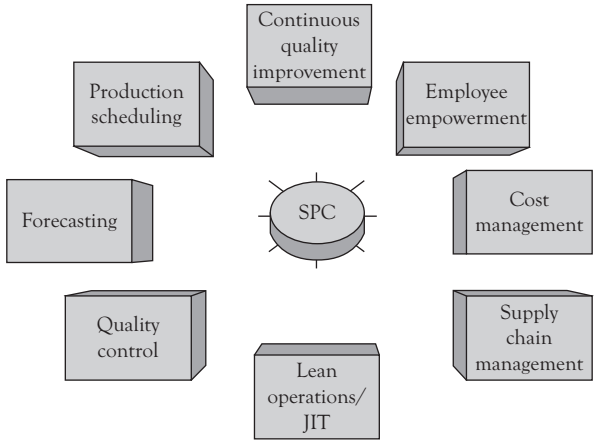

Figure 1.1 SPC adds value to business processes

organizations require their suppliers to use SPC in order to become preferred suppliers. SPC also can provide conclusive evidence for the effectiveness of continuous process improvement programs (Figure 1.1).

From Chaos to Control

Often the first step in implementing SPC for a process is to construct a control chart for the process as it currently exists. Frequently, this base line control chart will show the process to be chaotic and unpredictable or, to use SPC terminology, out of control. While this might come as a surprise to management, it often is not surprising to those charged with running the process, scheduling the process, and evaluating the quality of the product resulting from the process. However, the real issue is that prior to constructing the chart, the state of control of the process was unknown. How can one possibly make forecasts, schedules, or predictions about quality based on the unknown?

The control charts used by SPC to assess the state of control of a process should be created when the process is performing as designed. The team responsible for implementing SPC should assure that the equipment is in good working order, is being operated by a trained operator, the settings are correct, and the raw materials meet specifications. The resulting control chart is an empirical statistical model of how the process

can be expected to perform so long as it is operating as designed. The control chart reflects the expected level of variation for the process and we say that the process is operating in control. When other sources of variation occur, such as a defective lot of raw material, a machine malfunction, an incorrect setting, or a poorly trained operator, the control chart typically provides a signal indicating that the process is no longer performing as designed and we say the process is operating out of control.

SPC is designed to be used in real time. This means that samples (often referred to as subgroups) are taken from the process as the product is being produced, the samples are inspected, the data plotted on a control chart, and the state of control of the process assessed within as short a time span as possible. A stable, predictable, in-control process can drift out of control. However, with real-time SPC, the length of time it takes to identify this condition and correct the problem can be minimized. So, with SPC, we work with predictable processes and monitor those processes in real time to ensure that they remain in control. In this way, SPC significantly minimizes the uncertainty associated with those processes.

SPC and Production Scheduling

During the sales and operations planning process, production plans are created to meet sales forecasts and other organizational objectives. Production schedules are created to meet the production plans and are often based on standards contained in manufacturing master files. While these standards are sometimes based on historical averages, they are most often based on engineering assessments of the effective capacity—that is, the sustainable production rate with allowances for personal time and maintenance[2]—for the process.Creating production schedules from standards based on effective capacity assumes the process is behaving as it was when the production rates were set. Production schedules based on historical averages assumes the process is currently performing as it has done in the past. Both assumptions are simply acts of faith (and often vain hopes) when the state of control of the process is unknown. The only way to systematically monitor and assess whether these assumptions are valid is through the use of SPC.

A process proven to be in control through the use of SPC is predictable. A process shown to be out of control using SPC is unpredictable. A process running without SPC is an unknown quantity. So it should not be surprising that production schedules for processes whose state of control is unknown often are "not worth the paper they are printed on," as one production supervisor put it. Without the predictability that SPC provides, there is more chaos and uncertainty, more stress, extra meetings, missed schedules, and additional overtime, which contribute to increased cost, reduced productivity, excessive built-in allowances for uncertainty, and impaired employee satisfaction. Additionally, employee confidence in management and those ultimately responsible for drafting unrealistic production schedules may be affected.

SPC will not assure that a process always operates in a state of control and thus be predictable. However, SPC is designed to be run in real time, which will be discussed in more detail later in this chapter. This ensures that out of control conditions are detected in a timely manner and current information is made available to troubleshooters who are assigned to find and correct the problems that SPC indicates are present. Timely detection coupled with effective and timely troubleshooting and problem correction can prevent the out of control condition from persisting for long periods of time.

SPC and Forecasts

Forecasts are essential to organizational planning and decision making and, the more accurate the forecasts, the more accurate the plans and decisions. Inaccurate forecasts of revenue and profit can result in significant loss of stock value for a corporation. Inaccurate production and labor forecasts can cause significant disruptions within operations. The inaccuracies in operations forecasts can ultimately contribute to the inaccuracies in forecasts of revenues and profits. If we fail to produce what we forecast, revenues will suffer. If we fail to produce at the cost we forecast, profits will suffer.

Forecasts based on time series analysis of past data assume that the causal system that created variation in the value of what is being forecast will continue to do so in the same way in the future. While SPC cannot

affect the external influences that can alter the causal system (e.g., changes in consumer taste, availability of new technologies), it can increase the accuracy of forecasts by decreasing the variation in processes upon which the forecasts are based. When the causal system underlying a forecast is comprised of processes that are out of control, forecast accuracy is greatly diminished. Indeed, a term used to describe such forecasts is not worth the paper they are written on. How can a forecast based on unpredictable processes be anything but inaccurate?

Example 1.1

Why are We Always Missing Deadlines?

Once again the question arises in the staff meeting: Why are we late on so many shipments? The forecast called for the production of 100 products per hour by the process. Production records indicate this forecast was met. Yet, the product is not ready to ship. Investigation shows that much of the product produced is either awaiting inspection or has been rejected and is awaiting rework.

One problem is that the forecast was based on standard production rates, which assume and account for some standard defect rate. However, since the process is in an unknown state of control, there is considerable variation in defect rates, resulting in considerable variation in the rate of production of acceptable product ready to ship. In this case, considerably more defective product was produced than the forecast allowed for.

Late deliveries can be a source of customer dissatisfaction as well as hurting the profit and loss (P&L). Often the answer is that the product was produced on time according to the schedule based on the forecast. But instead of being in the finished goods warehouse ready to ship, some or all of the products are awaiting inspection by quality control (QC) or has been rejected and is awaiting rework. Worse yet, the process may be shut down while engineering and maintenance technicians try to determine why so much defective products have been produced. No wonder the production forecast wasn't worth the paper it was written on, and the actual P&L is worse than the pro forma.[3]

Process instability and poor capability of the process to consistently produce products that meet specifications can result in considerable variation in product quality. Variations in the lag time between production and inspection can make troubleshooting process problems more difficult. Implementation of SPC brings processes into control and can provide reliable estimates about the state of the processes. The result will be more reliable standard production rates that can support more accurate production forecasts. When combined with continuous improvement activities, SPC can help minimize process variation and increase the capability of the process to meet specifications resulting in an increased ability to meet forecasts and shipment commitments. More importantly, customers will be happier and the P&L will look more like the pro forma.

When SPC is used to bring the causal system processes into control, forecast accuracy will typically be increased as well. Because common cause variation is still present in an in-control process, it is impossible to provide perfect input to forecasting models. Perfection, while desirable as a goal, cannot ever be achieved in a forecasting model. However, perfection in a forecast is seldom necessary to achieve the objectives of the forecast. Most would agree that an accurate but imperfect forecast provides a much better basis for decision making than one not worth the paper it is printed on.

SPC and Quality Control

The output of processes must be assessed for quality in some way. Typical end-of-line inspection processes where the output is collected into lots and assessed using some form of acceptance sampling suffer from several flaws. The first flaw is the delay between the time a product was produced until the time the inspection occurs. I have observed cases where the lag period between production and inspection was measured in days. So, if a problem is detected in a lot, the process that produced the lot may have run in much the same way producing defective products throughout the entire lag period. This can result in a considerable quantity of potentially defective material, which must be subjected to more extensive inspection,

possible rework, downgrade, or scrap. I have observed plants where a great deal of space is occupied by pallets of material awaiting inspection. Frequently, these plants have large rework departments to sort through rejected lots of material and correct defects where possible. This excess inventory and non–value-adding operations are the result of uncontrolled processes and significant lag time between production and inspection.

A second flaw is that acceptance sampling plans simply provide a lot disposition (accept or reject) and, unlike SPC, cannot provide evidence about the state of control of the process that produced the lot. SPC, unlike acceptance sampling, controls the quality of the output by providing information to allow control of the process. SPC provides the means to develop capable and in control processes that produce product that is more uniform and predictable in quality.

SPC and Lean Operations or Just-in-Time

ASQ defines *lean* as "producing the maximum sellable products or services at the lowest operational cost while optimizing inventory levels" and *just-in-time* (JIT) as "an optimal material requirement planning system for a manufacturing process in which there is little or no manufacturing material inventory on hand at the manufacturing site and little or no incoming inspection."[4] These definitions make it clear that variation can be the enemy of both lean and JIT.[5] In the words of quality expert W. Edwards Deming, JIT "is sheer nonsense unless the process is stable. Unless it is stable (in statistical control), nobody knows who is going to need what or when he will need it."[6]

Excess inventory leads to increased cost. In order to understand the effect of SPC on lean and JIT, we must understand some of the reasons why inventories are required.

Buffer stocks are needed to provide a decoupling between processes so that variation in one process does not adversely affect the succeeding processes. Decreasing variation in the processes through the use of SPC decreases the need for buffer stocks.

Safety stocks are needed, in part, to protect against forecast errors and variation in demand for parts by internal processes. We have previously discussed the improvement in forecast accuracy as a result of using SPC.

However, if we use an accurate demand forecast to set procurement quantities, we must consider what variation exists in demand for the parts by the internal processes. If the standard scrap rate for a part is 2 percent, but the variation in this scrap rate is highly variable due to out of control processes, procurement of the forecast amount plus 2 percent will often lead to stockouts. To prevent this, excess safety stock is maintained. Using SPC to bring processes into control can reduce the need for these excess safety stocks.

SPC and Supply Chain Management

Safety stock is also used to provide protection against late delivery and receipt of defective materials from suppliers. In a supply chain, there are usually multiple upstream members in series for each purchased product. Variation in your direct supplier's processes creates variation in lead time, on-time delivery, and quality. Variation in each upstream supplier's processes has the same effect on their direct downstream customer. By the time the product gets to your organization, it has been subjected to multiple layers of variation creating the need for excessive safety stock. Extra safety stock means extra cost.

When each member of the supply chain uses SPC to monitor and control processes, the total variation observed from end to end in the supply chain is diminished, overall costs are reduced, quality is less variable, and deliveries are more likely to arrive on time. Frequently incoming inspection can be significantly reduced when suppliers submit evidence that their process are in control and capable. All of these benefits of SPC can increase customer satisfaction both for internal customers to the supply chain and to the ultimate customer. Because of this, a number of top manufacturing companies have mandated that their preferred suppliers implement and use SPC. This mandate should only be imposed after your company has implemented SPC for its own processes and is in a position to provide technical expertise and advice to suppliers as they work to comply with the mandate.

SPC and Costs

Implementing and operating a SPC program are not free. Resources must be invested in training, software acquisition, and implementation projects

in order to implement SPC, and processes whose base line control chart shows they are not in control must be brought into a state of control. This involves examining the entire process and correcting any problems that are found. Often parts that are worn, but have not yet catastrophically failed, must be replaced. Sometimes obsolete control systems must be updated. Greater consistency between lots of raw material might be needed necessitating negotiating with the current suppliers or developing new suppliers. Designed experiments may be required to optimize process settings. Additional operator training may be required. All of these activities require resources.

These and other issues must be addressed to bring the process into a state of control and all require resources and equipment downtime. However, these costs should be considered to be investments. Done properly as a part of the SPC implementation project, there will be a positive return on investment (ROI) derived from the reduction in variation in the process, fewer unplanned disruptions, less rework, and more consistent production output.

Near-Real-Time System

Several years ago I was assisting a client evaluate potential suppliers for aluminum extrusions. Using publically available information I was able to narrow the list of possible suppliers to three. I contacted each supplier and requested that they send me a copy of their quality manuals. The best candidate stated that they used SPC to control their processes and took necessary corrective action to investigate out of control conditions.

While on a site visit to the candidate's facility I asked the quality manager about the company's use of SPC. He took me to an operator station on one of the extrusion lines where I observed the operator periodically taking samples from the process, making measurements, and recording the measurements on a sheet of paper, which listed the specifications for the part being manufactured at the time. Upon further questioning, the quality manager said that once a week or so he gathered all of the data from the operator's stations and plotted it on control charts. He offered to show me the charts in his office. I asked what use the company made of the charts. The quality manager said that copies were sent to customers

who asked for them. Otherwise he kept them in a file in his office for several months before discarding them.

I did not recommend this company to my client because they were not really using SPC. They were plotting outdated data on control charts to satisfy specific customers. The charts played no role in monitoring and controlling the processes.

When operators or technicians take samples, make measurements in a timely fashion, and then plot them on a control chart manually or via computer, they have the information necessary to make a near-real time decision about the state of control of the process. When the chart shows that the process is in control, they know that no adjustment is necessary. When the chart shows that the process is out of control, they can take timely action to ascertain the nature of the problem and take the appropriate corrective action. When the data are not plotted in a timely fashion, long periods can elapse with the process running out of control. When this condition is recognized days or weeks after the assignable cause occurred, it is more difficult to trouble shoot the problem.

SPC and CQI Work Together

The successful implementation of SPC represents a significant improvement to quality and operations. Once implemented, SPC can be of significant value in identifying opportunities for continued improvement as well as providing a measure of the effectiveness of the continuous improvement projects. As the following example shows, it can also document the ineffectiveness of continuous quality improvement (CQI) programs also.

Example 1.2

A Tale of Two Hospitals

Hospital A uses SPC to monitor and control patient satisfaction with meal service. While the control chart showed the process to be in control and predictable, the average level of dissatisfaction with meals was considered to be excessive and represented an opportunity for

improvement. After collecting information from patients, dieticians, and nursing staff, the hospital instituted a program designed to improve patient satisfaction with meals. The control chart clearly indicated a significant reduction in the proportion of patients not delighted with their meals beginning at the period in which the improved process was launched. The chart documented more than a 30 percent reduction (from more than 10 percent to about 7 percent) in the proportion of patients not delighted with their meals. This is a case of an out of control signal on a control chart being a good thing because it confirms that the process was improved as the result of planned action. And not only does the chart clearly document the effectiveness of the improvement, but it provides a means of monitoring the process to assure that the gain is sustained.

Hospital B boasts that it has practiced CQI for a number of years. They also use SPC to monitor and control a number of processes in the hospital. However, the control chart used in the hospital to monitor overall patient satisfaction with the hospital shows that over the entire three-year time period covered by the control chart, the process has been stable. The hospital had initiated several quality improvement projects designed to improve patient satisfaction—the parameter plotted on the control chart. In this case, the control chart provides evidence that none of the improvements were effective. In the presence of a CQI program designed to improve a process, a stable control chart is an indicator that something is wrong with the CQI program.

The control chart for Hospital A is included in Figure 8.2.

Control and Minimization of Variation

SPC is designed to control and minimize variation in processes. As previously discussed, unpredictable processes can increase the need for inventory, increase variation in quality, reduce forecast accuracy, and increase costs. However, there are other reasons to be concerned about the control and minimization of process variation. The most important of these is that process variation creates variation in the quality of the product produced by the process. The more variation in the process, the more variation in the quality of the product.

Even when process variation does not result in the production of significant amounts of a product that is out of specification, the part-to-part and lot-to-lot variation within the specification can be troublesome to customers. Genichi Taguchi famously developed what is called the Taguchi loss function,[7] which quantifies the losses incurred by producing products that are not exactly at the specification target value. He showed that often unidentified losses are incurred when products are within specification but not exactly on target. The way to produce more products on target is to utilize SPC to appropriately center the process on the target value, reduce process variation, and monitor and control the process to keep it operating as designed.

Example 1.3

Total Molded Products

An injection molding facility began implementation of SPC in their processes. One process produced plastic panels for electronics enclosures. The engineers determined that part weight was a good proxy for the overall quality of the molded part. They began with a pilot study that showed the process to be out of control and yielded the following statistics:[8]

Mean part weight	43.86
Standard deviation	3.06

After completing the process of implementing SPC, the process was in control and yielded the following statistics:

Mean part weight	43.69
Standard deviation	1.21

The plant found that the production efficiency for this process increased as a result of the production of fewer defective parts and decreased downtime to troubleshoot problems.

The plant's customer for this product was delighted with the reduction in the standard deviation, which documented a substantial reduction in variation in the part. The customer employed an automated assembly process and the reduction in panel variation resulted in fewer jams of its assembly equipment and better fit and finish of the finished product.

SPC and Employee Empowerment

An unexpected benefit to a properly implemented SPC program is improved employee attitudes. SPC can be considered as a participative approach to QC when employees are trained to collect the samples, make the measurements, enter, or plot the data, assess the state of control of the process, and take appropriate action when they detect an out of control signal. Employees are empowered by SPC and experience a greater degree of control over their work environment.

One study[9] found some support for employees' greater feeling of control over quality and an improved attitude toward management. During implementation at the study facility, employees received training in SPC including sampling and measurement procedures, control charting, problem identification, problem solving, and they assisted in the development of standard operating procedures (SOP) for actions to take when out of control signals were detected. Employees also participated with management in developing SOPs for setting up and operating the process in order to reduce process variation caused by operator-to-operator differences. After SPC implementation, management emphasized the importance of operating the process according to the jointly developed SOPs. With SPC implemented in this way, it is not at all surprising that employees feel more empowered and have an improved attitude toward management.

Other studies have reported mixed results, but this is probably due to the method of implementation of SPC. An SPC program that is implemented with little production employee involvement is unlikely to have any effect on employee attitudes. However, one study[10] did find a number of effects associated with successful SPC implementations including increased number of production employees inspecting their own work, reduced production employee absenteeism, increased production employee efficiency, increased teamwork among employees, and increased employee participation in decision making.

Chapter Take-Aways

- SPC is not just a statistical tool. Its use can help organizations move from chaos to control. SPC can also be a solid partner with other organizational management approaches.

- SPC can increase the accuracy of production schedules and production forecasts.
- SPC is a powerful tool to help decrease process variation, product quality variation, and thereby improve overall quality.
- SPC is an essential partner to lean and JIT.
- Integrated throughout, SPC can dramatically reduce variation in lead time, on-time delivery, and product quality in supply chains.
- SPC can help identify targets for improvement and document the effectiveness of CQI programs.
- When used on-line and in real-time, SPC provides an opportunity to empower employees and give them more control over the quality of their work. Empowerment has been shown to improve employee attitude toward management.

Questions You Should be Asking About Your Work Environment

- *What activities in your organization would benefit most from decreased uncertainty that SPC can provide?*
- *Can SPC help jump start existing quality and efficiency improvement programs in your organization?*
- *Would your supply chain benefit from a reduction in variation?*
- *Could SPC increase your organization's ability to document the effectiveness of improvement projects?*

CHAPTER 2

Variation and What It Means to be in Control and Capable

To make a thing the way we want to make it is one popular conception of control.

—Walter Shewhart

Why is it that there is so much variability in what we do? Why can't we better predict how our processes will perform from day-to-day or even hour-to-hour? If you find yourself asking questions such as these, statistical process control (SPC) is a tool you will find useful. Let us begin with a discussion of variation.

Variation

More than 70 years ago, Walter Shewhart, the father of SPC, asked, "What can we say about the future behavior of a phenomenon acting under the influence of unknown or chance causes? I doubt that, in general, we can say anything."[1] Shewhart went on to discuss two types of variation: assignable cause variation and chance cause variation. We will also refer to chance cause variation as common cause variation and assignable cause variation as special cause variation—the terms most frequently encountered today. So, what is the difference between common and special cause variation?

Suppose you drive to work by the same route and at about the same time every workday. Sometimes you are lucky and make every light. Other days you miss most of them. Traffic is sometimes heavier on some days than others. These are examples of common cause variation and they can result in variation in the length of time it takes to drive to work. The

American Society for Quality (ASQ) defines common "causes of variation (as those) that are inherent in a process over time. They affect every outcome of the process and everyone working in the process."[2] It is the variation that exists in a process when it is operating as designed and, in the case of our example, these causes result in variation in travel time to work but that variation is predictable. That is, we can predict that the drive to work should fall within a certain range, which is determined by the common cause variation.

Suppose that one day, in addition to the traffic lights, traffic, and other common causes, we run out of gas. This additional source of variation is unusual and is referred to as an assignable cause. ASQ defines assignable cause as "A name for the source of variation in a process that is not due to chance and therefore can be identified and eliminated. Also called *special cause*."[3] Special causes can have a profound effect on a process and make it unpredictable. The range of times established when only common cause variation was present is out the window when one or more assignable causes are also present. Thus you can no longer predict how long it will take to get to work on a day when you run out of gas. The length of the drive will depend on a number of additional factors. Is there a gas station nearby? If not, how long will it take for your roadside assistance service to send help? Will a policeman stop to offer assistance? These additional factors are now paramount in how long it will take us to make our commute.

Process Variation: In and Out of Control

We say that a process is in control when "the variations among the observed sampling results can be attributed to a constant system of chance causes."[4] That is, the variation in the length of the drive to work is due exclusively to the identified common causes in the system, which include our luck with traffic lights and the amount of traffic.

We say that a process is out of control when "the variations among the observed sampling results cannot be attributed to a constant system of chance causes."[5] That is, the variation in the length of the drive to work is due to both the identified common causes IN ADDITION TO the assignable causes such as running out of gas.

So, we now understand the difference between common and assignable cause variation and what it means to be in control or out of control. But, what difference does it make? Let us continue with the driving to work example. Suppose you keep a record of your drive times and determine that on average it takes 57 minutes to get to work. There are two "outliers": drive times that appear to be significantly higher than the others, which you eliminate before doing your calculations so as not to overly affect the average. The outliers appear to be due to assignable causes—you ran out of gas twice while driving to work. With the outliers removed, you observe that the longest drive time is 67 minutes and the lowest is 47 minutes.

When someone asks about the length of your commute, you might respond that it is 57 minutes even though it would be more accurate to say it is between 47 and 67 minutes. If you want to assure that you are never late for work, you might decide to leave 67 minutes before start time. By doing so you assure that you will be either early or on time every day so long as only common cause variation is present.

But what about the outliers? If you really want to decrease the probability of arriving late for work, you should examine why these outliers (assignable causes of variation) occurred. Once you determine that both are due to your running out of gas, you might decide to change your refueling system. Instead of refueling only when the low fuel light comes on indicating your fuel level is alarmingly low, you might decide to check the gauge every afternoon before leaving for home and refueling whenever the gauge shows a quarter tank or less. This modification of the system should assure that you will never again run out of gas on the way to work.

Example 2.1

Evaluating Worker Productivity

A few years ago I was given a tour of a new automated warehouse. During the tour the warehouse manager showed me how he measured and managed stock picker productivity. A large chart was prominently displayed where each worker's productivity was displayed. Workers who fell below a specified number of picks per day were issued disciplinary warnings.

As the tour progressed, we stopped at a picking station where several conveyor belts moved overhead. Periodically the packages on one belt jammed and the picker was required to use a broom handle to clear the jam. The manager explained that this happened fairly often, but wasn't really a problem since the jams were easily cleared. Since clearing the jams obviously took time away from the picking job, I asked whether an adjustment was made in the picking standard for this station to prevent the picker from being reprimanded for a system's problem over which he had no control. The manager replied that no adjustment was necessary. Since the pickers were rotated daily, no one picker would stay on this station often enough to receive enough reprimands to trigger disciplinary action.

In this case, management was aware of a specific assignable cause yet still treated the situation as if the variation was due to common causes under the control of the picker. Does such a situation exist somewhere in your organization?

Knowledge about whether a process is in or out of control has other, more significant implications. Consider the heating, ventilating, and air conditioning (HVAC) system in your office. It consists of a number of components, but let us consider just the thermostat in this example. Suppose you wish to maintain the temperature in the office at 72°F year round. When the thermostat is operating in control, sampling the ambient temperature may reveal that it varies between 70° and 74°. You notice one day that it is particularly hot in the office although the thermostat is still set at 72°. You check the actual temperature and find it to be 80°. The maintenance technician finds the assignable cause—the thermostat has malfunctioned—replaces the device and brings the process back into control.

Suppose someone in the office is particularly sensitive to small variations in temperature. They are too warm when the temperature is 74° and too cool when the temperature is 70°. They assume the process is out of control and begin to manually manipulate the thermostat in an effort to stay comfortable. When the temperature is 74°, they adjust the thermostat to 68° to cool it down, Since the thermostat controls to within ±2°, it cools until the actual temperature reaches 66°. Now freezing, they readjust the thermostat to 74°, which results in a peak temperature of

76°. By overadjusting a process that is in control at between 70° and 74°(74° ± 2), the process now is performing between 66° and 76° (72° ± 6). The process variation is now three times greater than if the thermostat had been left alone.* This is an example of what can happen if all variation is treated as if it has an assignable cause. If the organization is not happy with the ±2° common cause variation in the process, an appropriate response would be to invest in a more precise thermostat that can maintain a set temperature to within ±1°.

W. Edwards Deming created an exercise to illustrate the dangers associated with tampering with a process that is in control. It is called Deming's Funnel Experiment.[6] In the experiment, a marble is dropped through a funnel onto a piece of paper on which a bull's eye is marked, and the location where the marble lands is marked on the paper. This is repeated many times first without moving the funnel (Rule 1 in Deming's experiment). Typical results are shown in Figure 2.1a. Next the funnel is adjusted after each drop according to one of several rules. In one rule, if a marble lands one inch above the bull's eye, the funnel is adjusted one inch south of its original position (Rule 2 in Deming's experiment). Rather than decreasing the variation, this adjustment after each marble results in a dramatic increase in variation as shown in Figure 2.1b. The same result can be expected when an overzealous machine operator measures each part that is produced by a machine operating in control and adjusts that machine based on each measurement. The performance of the machine as measured by the variation in the dimensions of the parts produced will be much worse than if the operator had left the machine alone.

The primary tool for determining the state of control of a process is the control chart. The control chart represents the process talking to you—telling you about its state of control, and when it shows the process is in control actually represents a kind of statistical model of the process. This model allows one to make predictions about the process. Control charts are discussed in Chapters 3–6.

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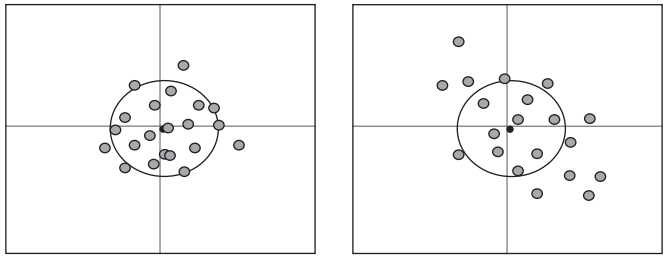
* This actually happened and the company responded by providing each employee with his or her own thermostat, which they could adjust at will. Everyone agreed that they were more comfortable. No one told them that the thermostats were dummies—not connected to the HVAC system.



(a) Rule 1 no adjustment (b) Rule 2 adjust after each drop

Figure 2.1 Results of rules 1 and 2 of Deming's funnel experiment

Source: A macro is available to conduct Deming's Funnel Experiment using Minitab at http://support.minitab.com/en-us/minitab/17/macros/macros-files/educational-macros/funnel/ . A video of the Deming funnel experiment is available on line at http://www.youtube.com/watch?v=9Z3o64FAtvA

Having determined that a process is in control, the next step is to determine how well the stable process is able to meet specifications. This is referred to as process capability analysis.

Capable

It is important to note that simply because a process is in control does not mean that process is capable of achieving the results we desire. A process that produces 100 percent defective product may be in control and predictable; however, no one would consider that to be a satisfactory result.

ASQ defines process capability as "A statistical measure of the inherent process variability of a given characteristic"[7] and assumes the process is in control. We can think of capability as measuring the ability of an in control process to meet specifications or expectations. We may derive a first order estimate of the capability of our commuting example by using the range. The current commuting example process is capable of providing a drive time between 47 and 67 minutes with an average of 57 minutes. The range for this process is 67 – 47 = 20 minutes.

But suppose we are not satisfied with having to leave 67 minutes before start time each day in order to minimize the probability of being late. We would like to spend more time with the family at breakfast. To reduce the time you have to leave before work starts (i.e., make the

process more capable), another change to the system is required. One alternative to consider might be to use the Metro Park-and-Ride system. You drive 10 minutes to a parking lot, board a bus that uses the high occupancy vehicle (HOV) lane, and delivers you to the downtown station in only 15 minutes. Your office is a 5-minute walk from the station. Your total "drive" time is now reduced to an average of 30 minutes. The new system also has a smaller range of transit times of 25–35 minutes or 10 minutes. To assure that you have the same on time arrival at work performance with the new system as with the old, you should leave home 35 minutes instead of 67 minutes before start time. This allows you to spend 32 additional minutes with your family and has the ancillary benefit of allowing you to read the paper or work while riding the bus instead of driving. We have improved the capability of the process by improving, or in this case redesigning, the system.

So how do we know what type of variation is present in a process and how do we measure process capability? These topics are discussed in Chapters 3 and 7, respectively.

Measurement Variation

Humorist Evan Esar once defined statistics as the "science of producing unreliable facts from reliable figures." The more common problem encountered in SPC is associated not with unreliable facts but unreliable figures. We are often too quick to assume that because we measured a value, it is a fact. However, there are significant potential sources of error associated with measurement processes of all types. If we ignore these potential sources of error, we are subject to the GIGO—garbage in; garbage out—effect and we try to produce reliable facts from unreliable figures.

Perhaps you have, as I have, weighed yourself at home, at the fitness center, and at the doctor's office on the same day. Never are the three weights the same. Consequently, I have doubts about knowing what I really weigh—the figures are unreliable. With SPC, it is vital that we have reliable data. So we conclude our discussion of variation with a discussion of variation in measurement or measurement error.

When we measure something—physical dimensions, customers' satisfaction, numbers of errors—the number we obtain is actually a function

of the actual value and the variation in measurement, often referred to as measurement error. The study of the science of measurement is referred to as metrology.[8] Measurement error consists of two parts. We refer to these two parts of measurement error as accuracy and precision when talking about physical measurement of things such as height, weight, and length. When talking about qualitative measurement of things such as customer satisfaction and employee attitudes, we refer to these parts as validity and reliability.

Accuracy and Precision for Dimensional Measurements

Accuracy is the characteristic of a measurement that tells how close an observed value is to a true value.[9] In the case of weighing myself on multiple scales and obtaining different weights, there is evidence that one or more of the scales is inaccurate. My actual weight is a true value. My weight as measured on my home scales may or may not be accurate. The only way to minimize error due to inaccuracy is by calibration against an accepted reference value. Were I to employ a certified technician who uses a set of reference standard weights that are traceable to the National Institute of Standards and Technology (NIST) to calibrate my home scales, I would be assured that error due to inaccuracy would be minimized.

"Precision is the aspect of measurement that addresses repeatability or consistency when an identical item is measured several times."[10] Precision, as applied to instruments used to measure physical dimensions, is comprised of two parts: repeatability and reproducibility (R&R). Repeatability is the ability of a single operator to obtain the same measurement value multiple times using the same measuring device on the same part. Reproducibility is the ability of separate operators to obtain the same measurement value multiple times using the same measuring device on the same part.[11] Precision for dimensional gauges is assessed through gauge R&R studies.[12]

Assuring the accuracy and precision of measurement systems is essential. Before beginning to collect data for SPC, examine the measurement system to assure that it has been properly calibrated and that a gauge R&R study has demonstrated its suitability for the task. These checks should be routine parts of the measurement process. Otherwise, you really have no idea whether the reported value is fact or fiction.

Example 2.2

Trendy Wire Company

A number of years ago I was working with a client that manufactured wire products such as power cords, connecters, and wire harnesses for consumer electronic devices. One process involved extruding a plastic insulating coating onto copper wire. Since the thickness of the coating determined how well the wire was insulated, it was a critical parameter that had to be controlled in order to maintain certification of the products by Underwriters Laboratories (UL). The problem was that the measurement data indicated there was excessive variation in the thickness of the extruded coating that had resulted in hundreds of miles of wire either being downgraded to a lessor standard and sold at a much reduced price or being sold as scrap.

Plant records showed that this problem had surfaced about three weeks previously and several process engineers had spent hours trying to determine what had changed in the process at that time. To this point, they had found nothing that seemed to correlate with the onset of the problem.

At this time, the plant did not use SPC. Indeed I had been asked to help them with SPC training and implementation. I thought that this process might be a good place to start, so I began working with the process engineers to determine the root cause of the problem.

We started by talking with the operators and assessing the measurement process. Micrometers were used by the operators to make thickness measurements which they used to make necessary adjustments to the process. Records showed that the micrometers were in calibration and that gauge R&R studies found that total RR was 10 percent of tolerance—a value the company considered to be acceptable. However, when I asked the operator to train me in making the measurements, I was unable to obtain repeatable results on a sample of the wire. Further investigation determined that the micrometer had been dropped about three weeks before which resulted in damage to the instrument. The operator did not notice any damage and failed to report the incident. When the micrometer was replaced, the problem disappeared.

Validity and Reliability for Qualitative Measurements

We often collect qualitative data from customers, suppliers, employees, and others using some form of survey methodology such as mail survey, telephone survey, on-line survey, or face-to-face interview. When doing so, we must be concerned with the validity and reliability of our measurement system. In this context, validity is the degree to which the method used to collect data actually measures what it is intended to measure. Reliability is the consistency of the method.[13] For an example of how to assess the validity and reliability of a survey instrument, the reader is directed to Sower, Duffy, Kilbourne, Kohers, and Jones.[14]

The use of previously validated scales is one way to address validity. However, one must exercise care to assure that the previous validation was conducted appropriately and that the constructs measured in its published use are identical to those you plan to measure. Scales found in the literature have generally been evaluated for reliability as well. However, one should always measure reliability each time the scale is used since reliability can vary with the population and sample being assessed.

Just as it is always dangerous to use dimensional measurement systems whose accuracy and precision are unknown, it is dangerous to use measurement scales whose validity and reliability are unknown. Spurious measurements incur two costs: the cost of making the measurement and the cost of being wrong about the true value of what is being measured. When using SPC, the cost of being wrong about the true value can be substantial because decisions are made about the state of control of the system being assessed. Spurious measurements can result in an organization failing to detect shifts, for example, in customer satisfaction because the survey instrument does not measure the key factors customers use to determine the quality of the products and services they receive.

Example 2.3

Maddie's Weenie Stand

Madeline Grace had experience in the food service industry and decided to unleash her entrepreneurial ambitions and open her own restaurant. She had leased a small storefront and opened Maddie's Weenie Stand.

She wanted to grow her business and realized that customer feedback was an important input. She started by using customer feedback cards, but very few customers bothered to fill them out. So she asked members of the local Chamber of Commerce how they obtained customer feedback. A local banker told her he used a survey he found on-line to measure the quality of the services his bank offered. He selected a random sample of residents from the telephone directory each month and mailed them a survey. He suggested she do the same.

So Madeline substituted Maddie's Weenie Stand for the bank's name on the survey form and began mailing 100 survey forms a month. She was disappointed to find that only about 5 percent of the forms were returned and the information they provided did not give her a clear direction about how to improve her products and services. So, she contacted the local university and ended up partnering with a management class adopting her business as a class project.

The students contacted the individuals on Maddie's mailing list and invited them to participate in focus groups. Maddie agreed to provide coupons for free hot dogs to all focus group participants. When the students reported their results at the end of the semester, Maddie was astounded.

Among the top reasons recipients failed to respond to the survey is that they were frustrated that the questions did not address the factors they considered important. Once this was discovered, the students asked the participants what factors they considered important in assessing the quality of a small specialty food restaurant such as Maddie's. One factor was product variety. Another was aesthetics—how the product was presented. Another was product freshness. The banker's survey did not ask about any of these factors.

The next semester, Madeline partnered with another management class to develop a survey instrument that addressed the factors that the focus groups showed were important to her customers. At the end of the semester the students presented Madeline with a survey instrument they had developed and pilot tested to assure that it was valid and reliable.

The first thing that Madeline found was that her response rate more than doubled with the new instrument. When she evaluated the information the surveys provided she noticed that a common theme was

that she did not offer enough product variety. She decided she would begin launching a new product—often one suggested by customers—each month. Those that sold well would become part of the standard mix. Those that didn't would be phased out. Several of the respondents to her survey had specifically mentioned Chicago-style hot dogs, so that was her first new product.

Her new strategy paid off. Business began increasing at a more rapid rate as shown by her run chart (Figure 2.2) and repeat customers increased dramatically. Asked what she learned from all of this, she replied: "One size does not fit all in hot dogs or survey instruments. You have to be sure you are asking the right questions of the right people and that you react to the input you receive in an appropriate way." Put another way, you must always be sure that your survey instrument is valid and reliable for your intended use then use the information it provides to guide business decisions.

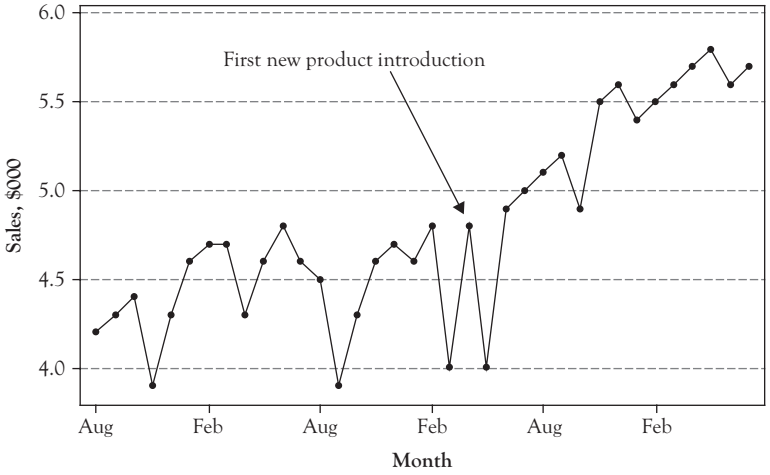


Figure 2.2 Run chart of sales

Source: Made using Microsoft Excel™.

Assessing the validity and reliability of survey instruments requires extensive knowledge and skills. In our example, Maddie was well advised to seek assistance in assessing her survey instrument.

Using measurement systems whose accuracy and precision or validity and reliability have not been assessed can lead to considerable waste of time in attempting to control and improve processes. In addition, they may lead to poor decisions that may do more harm than good. When employing SPC, always assure that you have properly assessed the measurement systems that will provide the data on which decisions are made.

Chapter Take-Aways

- All processes contain variation. Variation in processes can result from common causes and assignable causes.
- A process with only common cause variation present is predictable and is referred to as being in control. Overadjusting an in-control process increases variation.
- A process that contains assignable causes of variation is unpredictable and is referred to as being out of control. The root cause(s) of assignable variation must be determined and appropriately addressed in order to bring an out-of-control process into a state of control.
- In control does not mean that the process is meeting expectations. That is measured by process capability.
- Capability refers to the ability of an in-control process to meet expectations.
- Measurement processes are also subject to variation. Measurement variation is variation that derives from the process used to measure a characteristic. For physical measurement systems, accuracy and precision must be assessed. For qualitative measurement systems, validity and reliability must be assessed. Using a measurement system whose variation is unknown is akin to taking measurements with a rubber ruler.

Questions You Should be Asking About Your Work Environment

- *How many of your processes can be said to be predictable? If less than 100 percent, what would be the value of making all processes predictable?*

- *Do all of your processes consistently meet all expectations? If not, what would be the value of making all of your processes capable?*
- *Are all of your measurement systems regularly assessed? If not, how do you know that you are not being provided with "unreliable facts" from those systems upon which you are basing decisions?*

CHAPTER 3

Introduction to Control Charts

Uncontrolled variation is the enemy of quality.

—W. Edwards Deming

A control chart is defined as a "chart with upper (UCL) and lower (LCL) control limits on which values of some statistical measure for a series of samples or subgroups are plotted. The chart frequently shows a central line (CL) to help detect a trend of plotted values toward either control limit."[1] Note the absence of any mention of specification limits in this definition. Specifications represent the organization "talking" to the process—that is, telling the process what the organizations desires. A control chart represents "the process talking to the organization"—telling the organization what the process can do. Specifications should generally not be included on a control chart. The general form of a control chart is shown in Figure 3.1.

The CL represents the mean of the distribution for the statistical measure being plotted on the control chart. The distance between the UCL and LCL represents the natural variation in the process. The UCL is generally set at 3 standard deviations (a measure of the variation in the process output statistic plotted on the control chart—see Appendix A) above the CL and the LCL is generally set at 3 standard deviations[2] below the CL. The parameters upon which the control limits are based are estimated from an in-control reference sample of at least 25 data points.

In Chapters 4, 5, and 6 we will discuss specific types of control charts, how to select the appropriate control chart for the job, and how to use statistical process control (SPC) software such as Minitab 16 and Northwest Analytical Quality Analyst 6.3 to construct and use the charts. In this chapter, we will discuss the general idea—that is the theory—of control

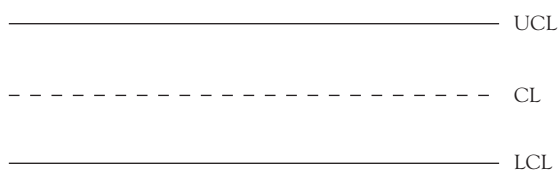


Figure 3.1 General form of the control chart

charts. To illustrate this discussion, we will use the control chart for individual variable measurements, which is based on the normal (bell-shaped) distribution, but the general theory we discuss in this chapter applies to all types of control charts discussed in the subsequent chapters. We will also discuss appropriate ways to go about implementing SPC.

Before beginning the next section of the chapter, readers with no previous training in statistics should read Appendix A, Bare Bones Introduction to Basic Statistical Concepts. Appendix A is short and to the point. Reading it first will provide the necessary background to understand the terminology and concepts discussed in the next section of this chapter and in the succeeding chapters.

General Theory of the Control Chart

"A control chart is used to make decisions about a process."[3] Specifically, a control chart is designed to determine what kind of variation exists in the statistical measure being plotted. If that measure is a key process characteristic, we can then say that a process is either in control or out of control relative to that characteristic. The term in control means there is only common cause variation present. Out of control means that there is assignable cause variation present in addition to the common cause variation. A process that is in control is predictable; a process that is out of control process is not predictable.

When we collect data from a process in order to create a control chart, we will find that some variation exists. This variation can be shown graphically in the form of a distribution. Perhaps our data can be described by the distribution shown in Figure 3.2.

This distribution is symmetrical, with half of the area on either side of the highest point of the curve. The highest point of the curve is

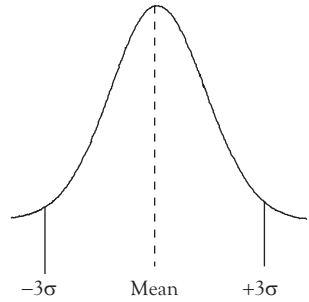


Figure 3.2 Normal distribution

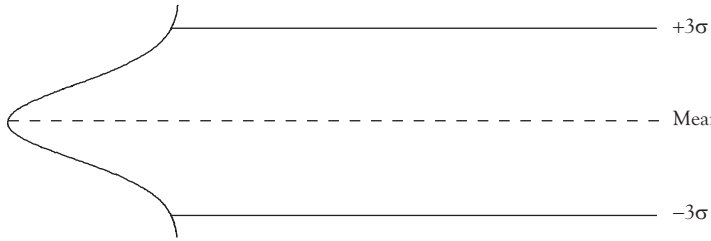


Figure 3.3 Normal distribution tipped on its side

located at the mean or arithmetic average of all of the individual values in the distribution. Most of the values are clustered near the mean with increasingly fewer values as we approach the tails of the distribution. We can mark the lines that represent 3 standard deviations above and below the mean on the distribution.[4] The majority of the values in the population represented by this distribution can be expected to fall between the 3 standard deviation lines and generally be distributed equally on either side of the mean. We will use the Greek letter sigma (σ) to represent the standard deviation.

In Figure 3.3 we tip the distribution on its side and extend the lines marking the mean and 3 standard deviations above and below the mean.

Finally we remove the normal distribution, relabel the mean line as the center line (CL), the +3 standard deviation line as the upper control limit (UCL), the –3 standard deviation line as the lower control limit (LCL) and we are left with a control chart as shown in Figure 3.4 (compare Figure 3.4 with Figure 3.1). We refer to this control chart as a control chart for individuals meaning that the chart is suitable for use with individual values that are normally distributed.

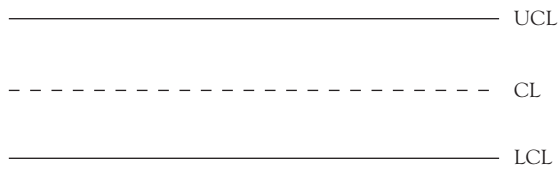


Figure 3.4 Control chart for individuals

Setting 3σ UCL and LCL is a standard practice when using control charts. However, it is possible to create control charts with UCL and LCL set at 2σ, 4σ, or any other value the user determines to be best. When setting control limits below 3σ, a greater number of false signals will be obtained. However, when the cost of investigating a false signal is far less than the cost of a missed signal, 2σ control limits might be warranted. When the cost of investigating a false signal greatly exceeds the cost of missing a signal, then 4σ control limits might be best. Changing control limits to some value other than 3σ should be the result of a clear rationale and a careful analysis of the trade-offs involved.

Now, what should we plot on our chart? The first step in the process of creating a control chart is to identify the statistical measure or measures that best represent the process. These are sometimes called key quality characteristics (KQC) or key performance indicators (KPI). There are many characteristics in a process that can be monitored. The trick is to identify the really significant ones that are good measures of the process and are meaningful for our purposes.

Then we collect data from the process and examine the data to determine the appropriate control chart to use and to check to be sure whether the assumptions for that control chart are satisfied. At least 25 observations from the process should be used in this step although a larger number of observations will result in a better estimate of the process parameters.[5]

The next step is creating the control chart. Remember, for the purpose of this discussion we will be using the control chart for individuals. Subsequent chapters will discuss other types of control charts. Then we construct the chart and plot the data on the chart. For our purposes, we will use statistical analysis software to do this. There are several advantages to using software rather than constructing and maintaining control charts

by hand. So long as the data are entered correctly, the software will not make calculation errors and all points will be accurately plotted on the chart. Additional benefits include getting a professional looking chart and the ability to do additional analysis of the data easily. The major drawback to using software to construct control charts is that the software will create charts and analyze data according to your instructions. If you lack the knowledge to tell the software the right things to do, you will obtain wrong and misleading results.

Example 3.1

The Tiny Mountain Coal Mine

Suppose you manage a small mining process that produces coal. The only real characteristic of interest to you is how many tons of coal are produced per week, so this is the statistical measure to be plotted. You have been dismayed with what you consider to be the excessive variation in the amount of coal produced per week. You would like to decrease the variation and increase the total output per week. You have determined that SPC is an appropriate tool to incorporate into your improvement process. You have collected output data for 45 consecutive weeks in Table 3.1 arranged chronologically.

Perhaps the only sense we can make of the data in this form is that production seems to range from 6 to 14 or so. We now enter these data into Minitab 16, a statistical analysis software package, in order to learn more about what the data are telling us.

We believe that a control chart for individuals[6] would be the right chart to use but we understand that this chart is sensitive to data that are not distributed normally.[7] So we use Minitab 16 to examine the distribution of the data, which is also shown in Figure 3.5. The histogram shows that data appear to be approximately normally distributed, so we will proceed with the construction of the control chart for individuals shown in Figure 3.6. We can see from the chart CL that the mean number of tons of coal produced during this 45-day period is 10.23. Most SPC software sets the UCL and LCL at 3 standard deviations from the CL unless instructed otherwise, so the chart shows the

UCL is 17.40 and the LCL is 3.06. The next question is "What else does the chart tell us about the process?"

Table 3.1 Tons of coal produced per week arranged in time series

Day	Tons of coal	Day	Tons of coal	Day	Tons of coal
1	7.2	16	12.0	31	9.6
2	8.5	17	11.6	32	10.5
3	12.1	18	9.9	33	13.8
4	10.0	19	11.1	34	10.4
5	14.3	20	6.4	35	8.9
6	11.6	21	10.4	36	7.2
7	9.1	22	8.8	37	10.0
8	9.7	23	12.6	38	12.1
9	7.5	24	9.9	39	9.5
10	11.6	25	4.5	40	11.3
11	8.8	26	10.4	41	6.7
12	13.5	27	9.4	42	10.5
13	10.2	28	11.4	43	8.4
14	11.7	29	10.4	44	9.7
15	10.5	30	15.5	45	11.5

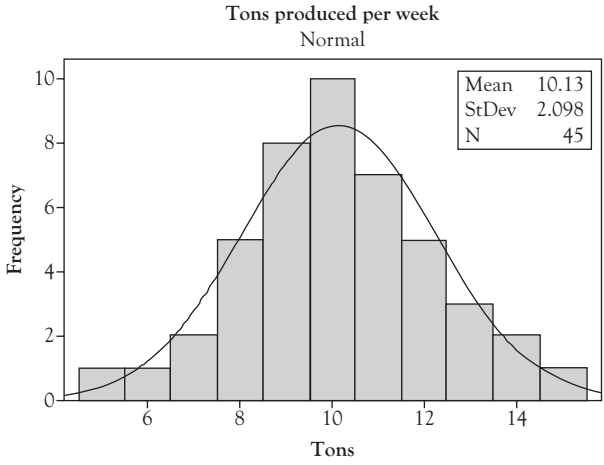


Figure 3.5 Data entry and histogram using Minitab 16

Source: Created using Minitab 16.

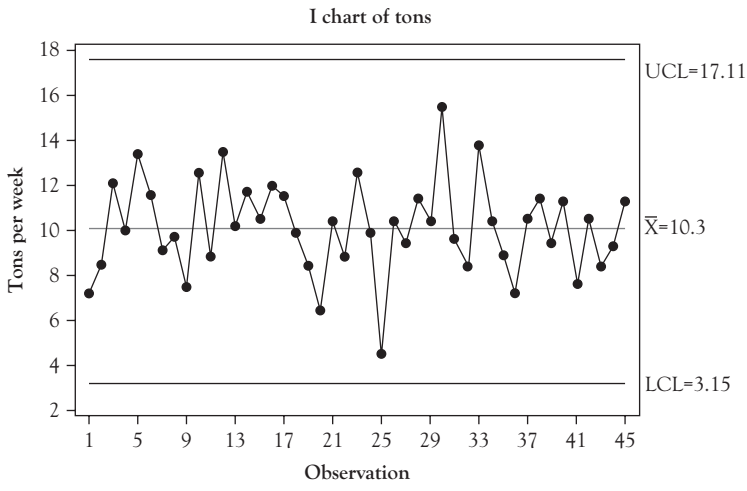


Figure 3.6 Control chart for individuals for tons of coal per week

Source: Created Using Minitab 16.

Control Chart Signals

Control charts represent the process talking to you—telling you how it is behaving. The value of a control chart depends upon our ability to read and understand what the process is saying. The chart in Figure 3.6, for example, is telling us that this process is in control—only common cause variation is present. We know this because there are no signs or signals that appear to be nonrandom. Because the control chart shows that the process is in control, we are comfortable using these control limits to monitor and control the process ongoing.

Are we 100 percent certain that this is a true message—that the process is actually in control? The answer is no. There is the possibility that nonrandom variation is also present and that we are missing it. However, that risk is small, so we behave as if we know with certainty that the process is in control. We should be aware of this risk, but trust the chart.

There are a number of sets of rules defining patterns on a control chart for determining that a process is out of control. Most software products used for SPC allow the user to specify which rules to use as shown in Figure 3.7. In this section, we will discuss the more commonly used rules for judging whether a process is out of control. Using a combination of

Example 3.2

Risk and Certainty

Often in our daily lives we behave as if we know something with certainty when actually there is a measureable risk that what we think we know is false. The smaller the risk, the more appropriate is this behavior. After all, there are few certainties in life. Among them, according to some sources, are death and taxes. In everything else, there is uncertainty (risk) at some level.

Assume you are playing a game with a friend. He flips a coin, and for every head you owe your friend a dollar. For every tail he owes you a dollar. You know that the odds of a tail (you win) for a fair coin are 50/50 (probability = 0.50) for each flip. The first flip lands heads, so you pay your friend a dollar. So does the second, and the third. After how many successive flips resulting in heads will you decide that the coin is not a fair coin? If you stop playing the game after 5 heads in a row (and a payment of $5 to your friend), you have behaved as if you know this to be certain even though there is 1 chance in 32 that you are wrong. This probability is so low that you behave as if you know with certainty that the coin is not fair. You are unwilling to risk another dollar by continuing to play the game in the face of the results you have observed.

The same logic applies to reacting to out-of-control signals on a control chart. There is a probability that the signal is false, but because the probability is low, we react as if we know with certainty that the process is out of control.

the one-point rule and the pattern rules will minimize the probability of reacting to a false signal or failing to react to a real signal.

The Single Point Rule

The basic out-of-control signal on a control chart is one point that is above the UCL or below the LCL. Figure 3.8 shows a control chart used

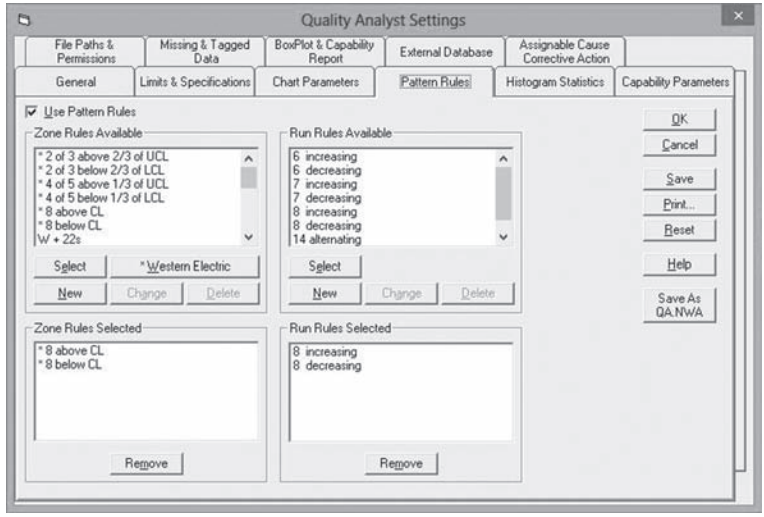


Figure 3.7 Screen for selecting pattern rules in NWA Quality Analyst 6.3

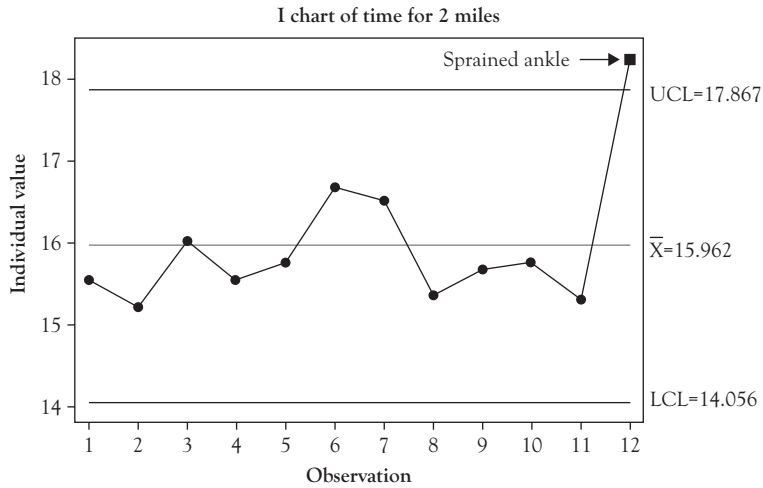


Figure 3.8 Process out of control—one point beyond UCL

Source: Created using Minitab 16.

by a recreational runner to monitor his time over the same two-mile route. The 12th reading on the chart is above the UCL indicating the process is out of control. The software has flagged this point by showing it as a red square rather than a black dot. The runner has investigated the

reason for the out of control signal and entered it as a comment on the chart.

The types of problems triggering this signal tend to be those that develop or manifest suddenly such as changing to a defective lot of materials, an inexperienced operator replacing a well trained one, catastrophic failure of a machine part, change in a machine setting, or rapid change in an environmental condition.

One point outside the control limits when the control limits are set at 3σ above and below the mean will yield very few false signals. However, it sometimes will fail to provide a signal when a significant change has occurred in the process. For this reason, we supplement this rule with additional rules referred to as run rules. Run rules are designed to detect assignable cause variation even when there is not a single point outside the control limits of the chart.

Run Rules

We will use two run rules. The first of these is a run of eight points on a rising or falling trend. This rule can create an out-of-control signal even if there are no points outside the UCL or LCL. Figure 3.9 illustrates this rule for a falling trend in the part weight of an item produced by a molding process. Points 10 through 17 show a falling trend in the part weight, indicating the process is out of control. The operator has investigated the reason for the out of control signal and entered it as a comment on the chart. The rule works in exactly the same way for a rising trend.

The types of problems triggering this signal tend to be those that develop and worsen over a period of time such as a heater failing resulting in a gradual drop in process temperature, a loose limit switch that changes position slightly with each repetition, gradual operator fatigue, or gradual buildup of waste material affecting the seating of parts in a fixture.

The second run rule we will use is a run of eight points above or below the CL. This rule, sometimes referred to as a pattern rule, also can create an out-of-control signal even if there are no points outside the UCL or LCL. Figure 3.10 illustrates this rule for a eight points falling above the CL in a chart plotting the monthly total output of silver from a refinery.

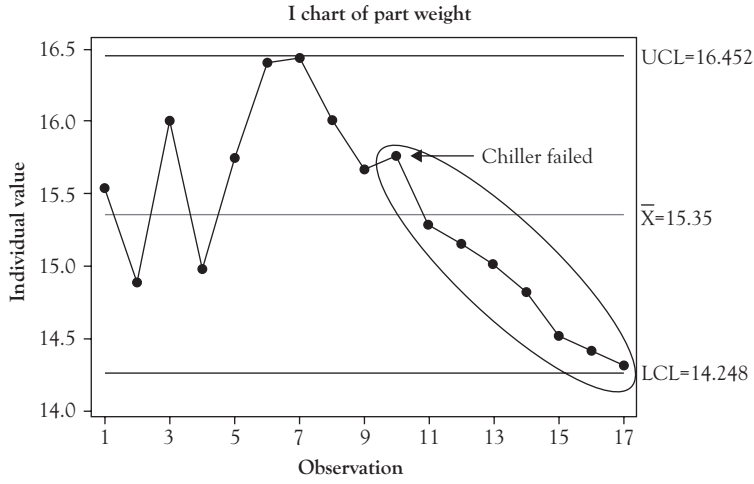


Figure 3.9 Process out of control—eight points on falling trend

Source: Created using Minitab 16.

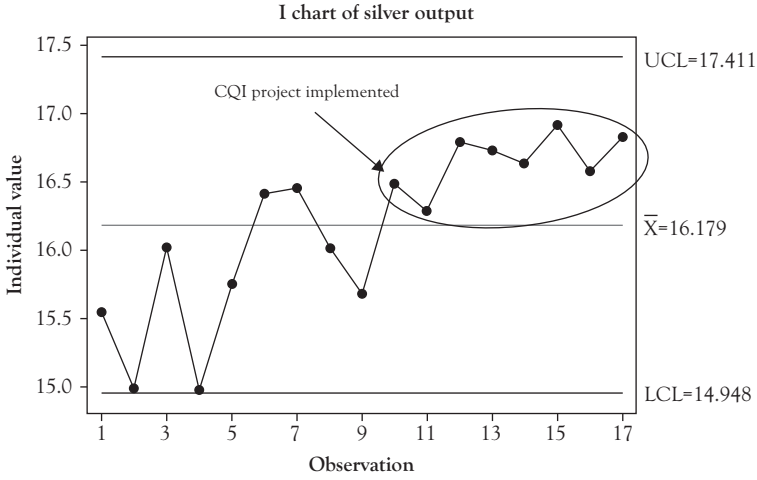


Figure 3.10 Process out of control—eight points above CL

Source: Created using Minitab 16.

Points 10 through 17 all fall above the CL of the control chart, indicating the process is out of control. The operator has investigated the reason for the out-of-control signal and entered it as a comment on the chart. In this case, since the signal represents a desired and planned improvement to the process, the control limits should be recalculated using the data beginning

at point 10. The rule works in exactly the same way for eight points falling below the CL.

The types of problems triggering this signal tend to be associated with significant shifts in some part of the process such as switching suppliers for a key raw material, making a known change to the process, changes of operator or shift, or failure of a machine part.

Zone Rules

The combination of using control limits set at 3σ, and using the single point rule with the run rules discussed above usually is sufficient to simultaneously minimize the probability of observing a false signal and missing a true signal. There are additional rules referred to as zone rules that are sometimes used to decrease the probability of missing a true signal. Caution must be taken not to impose such a large number of rules that interpretation of the control charts in real time by operators becomes overly complex.

To use the zone rules, the control chart area between the UCL and LCL is divided into sections corresponding to 1σ and 2σ above and below the CL. The 1σ lines are the upper and lower inner limits (uil/lil). The 2σ lines are the upper and lower warning limits (uwl/lwl). One zone rule signal is when two of three consecutive points fall within the 2σ (uwl/lwl) zone on either side of the CL. Figure 3.11 shows this signal at point 6 (marked (a) on the chart). Another zone signal is where four of five consecutive points fall within the 1σ (uil/lil) and 2σ (uwl/lwl) zone on either side of the CL. Figure 3.11 shows this signal at point 34 (marked (b) on the chart).

Other Nonrandom Patterns

The previous sections of this chapter discussed well-defined rules for determining that a process is most likely out of control. However, any nonrandom pattern can also provide a valid out-of-control signal. Sometimes, these nonrandom patterns may exist without any of the formal rules being violated. Sometimes, a formal rule is violated but the nonrandom

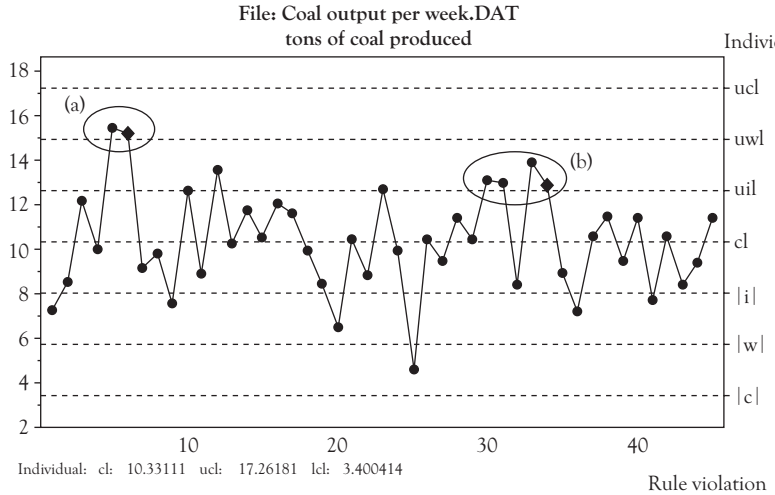


Figure 3.11 Process out of control—zone rules

Source: Created using NWA Quality Analyst 6.3.

pattern provides extra insight into possible causes of the out-of-control condition. Example 3.3 provides an example of a nonrandom pattern coupled with six single point out-of-control signals.

Example 3.3

Shift-to-Shift Variation Pattern

An injection molding company had just started implementing SPC in their processes, which ran 24 hours a day on three shifts. Typically, they collected data to use to construct the control charts on first shift since that was most convenient for the quality engineers. Before collecting the data, a cross-functional team comprised of quality engineers, process engineers, maintenance technicians, and operators inspected the process to be sure that the equipment was in good working order, raw materials were within specifications, and operators were trained.

The engineers were pleased that the process was in control when they analyzed the first 25 data points. They used these data to construct a control chart for the process. They provided operators training in sampling, testing, recording the data on the control charts, and

detecting out-of-control signals. They then started a pilot implementation of SPC for this process.

After a few days, it was clear from the chart in Figure 3.12 that something was wrong. Instead of the nice, in-control chart they observed initially, there were points beyond the control limits and a disturbing cyclical pattern that was clearly nonrandom. The cycles correlated with changing shifts. It appeared that second shift produced systematically higher part weights and third shift produced systematically lower part weights when compared with first shift.

The company employed a setup technician on each shift who was responsible for setting up the molding machines and troubleshooting problems that might arise. All three setup technicians were very knowledgeable, were known to be diligent workers, and had fairly long tenures in the organization.

The first step the quality engineer took to get at the root cause of the problem was to visit each shift and talk with the setup technicians. Each setup technician related the same story when asked what the biggest problem they faced in doing their jobs. Each said that their biggest problem was setting the machines properly at the start of each shift. The previous shift always ran the machines incorrectly.

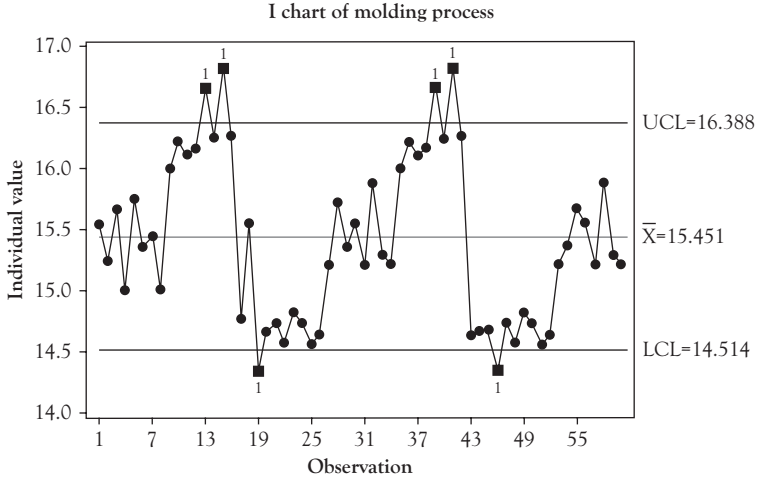


Figure 3.12 Pilot implementation control chart

Source: Created using Minitab 16.

The cause of the problem was now clear. All three setup technicians had their own ideas about how the machines should be run. Each was very diligent about adjusting the machine settings until the process was running optimally according to their idea about what optimal meant. This was not a case of incompetency or lack of diligence. All three setup techinicans was experienced and worked diligently to do their best for the organization. Deming often said that doing your best is not good enough. You must know what to do and all three setup technicians thought they knew what to do. The problem was a lack of coordination, which is a management issue and not an operator or setup technician issue.

The next step was to get all three setup technicians together on one shift. The quality engineer coordinated experiments designed to arrive at the true optimal setup conditions for the process. Once these were determined and agreed to, they were written up and signed by each setup technician. These documents became the standard operating procedures (SOP) for setting up this process.

The end result? The process was found to be in control. The problem with this process was solved and the quality engineer learned a lesson that she now applied when implementing SPC on other processes.

Action to be Taken Upon Seeing an Out-of-Control Signal

Whoever is responsible for taking samples, collecting the data, and entering that data on control charts must be taught not only how to read the charts but what to do when they observe an out of control signal. There is no standard SOP for this. Appropriate actions vary depending upon organizational decisions and factors. Among these are:

- Who collects the data and plots it on the control charts—that is, who controls the charts? Operators? Inspectors? Quality technicians?
- What authority has management provided to the person controlling the chart?

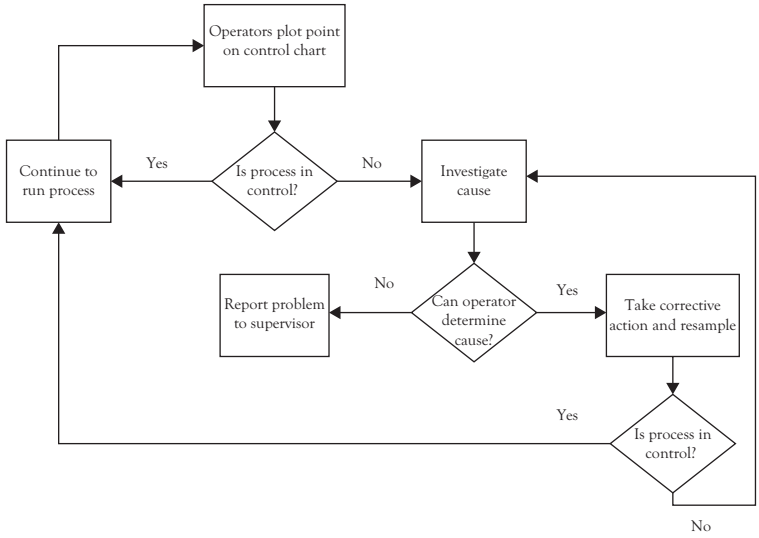


Figure 3.13 Action plan for responding to an out-of-control signal

- What resources does the person controlling the chart have available?
- How does the person controlling the chart communicate with others who need to know and who are available to assist in troubleshooting problems?

Figure 3.13 illustrates an example of a simple decision diagram to guide an operator tasked with maintaining the control chart for a process.

Implementing SPC

Implementing SPC involves much more than just creating control charts. When not properly implemented, results will be disappointing to the organizations. Proper implementation is a key to the success of SPC. The basic steps involved in implementing SPC are:

- Answer the questions: Why am I interested in implementing SPC? What is the purpose of the implementation? What do I expect the results to be?

- How will we run the SPC program? Will it be a quality department effort where quality technicians periodically sample the process or will the process operators collect the data and plot it on the control charts?
- Select and train the implementation team. The level of training will vary from basic SPC skills to advanced proficiency in SPC. There should be at least one or more highly trained SPC expert in the organization to support the initiative.
- Many organizations find that providing hands-on experience is a vital component of training. This can be done by conducting a pilot SPC implementation on a selected process as part of the training.
- Select the process and identify the KQC(s) that is the best measure of process performance.
- Insure that the measurement system to be used is accurate and reliable.
- Determine the sampling frequency, sample size, and rational subgroup.
  - Sampling frequency is often a balance between efficiency and effectiveness. Too frequent sampling can be expensive and a wasteful use of resources. Samples taken at large intervals can allow an out of control condition to persist too long.
  - Sample size also involves a balance between resources and effectiveness. Larger samples provide better information, but this must be balanced against the cost of sampling and testing.
  - Shewhart's rational subgroup concept is usually satisfied by taking consecutively produced samples for testing. Alternatively, random samples may be taken from all of the output of the process since the last sample was taken.
- A cross-functional team should examine the process to determine that it is operating as designed. The team should ensure that the equipment is in good repair, adjusted properly, and set up to design specifications, raw materials meet specifications, and that the operators are properly trained. Then collect

real-time data from the process to construct the initial control chart. At least 25 samples should be used.

- Examine the initial control chart for out-of-control signals. If none are present, this chart represents the current state of the process when operating in control. If signals are present, each should be investigated, the assignable cause addressed, and a new chart should be constructed using additional data.
- Establish the resulting chart as the "standard" chart for the process and establish a set of rules for reacting to out-of-control conditions.
- Follow-up to insure that the SPC process is being maintained properly and appropriate action is taken when an out of control signal is detected.
- Assess the improvements gained from implementing SPC. How do the improvements compare to the original expectations?
- Incorporate what you have learned into plans for continuous improvement of the process and plans for the expansion of the use of SPC.

It is better to start implementing SPC on a single process rather than trying to do so for all processes simultaneously. This provides the implementation team the opportunity to gain experience and confidence on a small scale before tackling the entire operation. As the number of people with SPC implementation knowledge and experience grows, it is much easier to implement SPC on multiple processes simultaneously.

Chapter Take-Aways

- A control chart contains upper (UCL) and lower (LCL) control limits and a central line (CL). Values of some key statistical measure for a series of samples or subgroups are plotted on the chart.
- A control chart represents the process talking to the organization—telling the organization what the process can do.

- Specifications represent the organization talking to the process—telling the process what the organizations desires. Specifications should generally not be included on a control chart.
- Control charts are based on some probability distribution.
- When an assignable cause variation is present in a process, signals will be observed on the control chart that indicate the process is out of control. Appropriate action should be taken immediately to identify the root cause of the signal and eliminate it from the process.

Questions You Should be Asking About Your Work Environment

- *Are your processes talking to you? Is their message one of control or chaos? If the latter, what would be the value of reducing the chaos and replacing it with control?*
- *Implementing SPC is not easy. The implementation process requires resources and expertise. What would an investment in SPC be expected to return in order to be considered a profitable investment?*

CHAPTER 4

Basic Control Charts for Variables

The idea of control involves action for the purpose of achieving a desired end.

—Walter Shewhart

Data used to create SPC control charts can be divided into two basic types: attributes and variables. Attribute data are go/no-go or count information. Examples include the number of defective units, the number of complaints received from dissatisfied customers, and the number of patients whose meals were delivered more than 15 minutes late. Control charts for attribute data will be the subject of Chapter 6. Variable data are continuous measurement information. Examples include measurements of height, weight, length, concentration, and pressure (psig). Control charts for variable data are the subject of this chapter and Chapter 5.

Individual and Moving Range Control Charts

Chapter 3 used the chart for individuals (I-chart) to illustrate the theory of the control chart. The I-chart is a variable control chart. In this section, we will add the moving range (MR) chart, which is often used in conjunction with the chart for individuals. This section will also use a different type of example to illustrate the range of uses for the I-chart.

There are many situations where the logical sample size for measurement is a single value. Examples include:

- Measurements per unit of time of the output from a process. Examples used in previous chapters were the volume of sales per month, the number of tons of coal produced per week by

a mine, the monthly output of silver from a refinery, and the time to run 2 miles. Other examples include overtime costs per week, and the number of gallons of gasoline sold per week.

- Economic data. Examples include gross national product by month, unemployment rates, and the Institute for Supply Management's (ISM) Purchasing Managers Index (PMI).[1]
- Processes where a key quality characteristics (KQC) is measured for every item produced. Measurement of every unit may occur because of long cycle times, or because of the use of automated measurement systems. Examples include measurements of wall thickness for molding processes that take several hours per unit, and fill weight for food containers from an automated process.
- Situations where measurements are dispersed over time. An example would be the percentage of moisture in shipments of solvent received from a supplier. Shipments may arrive on an irregular basis with an average of 4 to 10 days between shipments.

Control charts for individuals are sensitive to nonnormality. The data should be analyzed to determine that the distribution is approximately normal before using the I-chart.

The I-chart alone is superior to a run chart because the control limits on an I-chart allow the user to determine when observed variation is significant. That is, the I-chart allows the determination of the state of control of the process while the run chart does not. A run chart is a "chart showing a line connecting numerous data points collected from a process running over time,"[2] and can be useful for visually depicting changes in a process over time. The PMI is an indicator of the economic health of the U.S. manufacturing sector published monthly by ISM. Figure 4.1 shows a run chart of the PMI by month from November 2011 to April 2013. Some variability is evident, including some large swings between points 10 and 12 and between points 18 and 20, but there is no way to determine if these are significant. For this we need to use an I-chart.

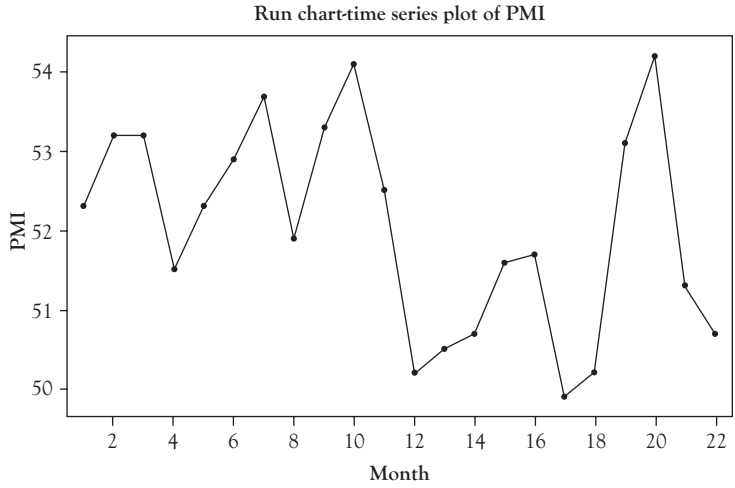


Figure 4.1 Run chart for PMI data

Source: Created using Minitab 16.

The I-chart for the same data used in Figure 4.1 is shown in Figure 4.2. This chart indicates that the PMI data are in control—that is only common cause variation is present.

However, in order to determine the variability of the process, another chart is used. This is called the moving range chart. Usually the MR is determined by calculating the difference between two successive points on the individuals chart. To be most useful, both I-chart and MR chart are used together. The MR chart plots the difference in successive individual values. Figure 4.2 shows the I-chart and the MR chart. The first point plotted on the MR chart is the difference between points 1 and 2 on the I-chart. The control charts show that the swings noted on the run chart are not significant and the overall process is in control. Notice that the distance between the central line (CL) and upper control limits (UCL) is greater than that between the CL and LCL on the MR chart. This is because the LCL cannot always be set at 3 standard deviations below the CL because that would result in a negative value for the range, which is mathematically impossible. In this case, the lower control limit (LCL) is set at zero—the lowest possible value for the range.

Since the data plotted here are economic data and do not represent a process where it is possible to control the inputs, the interpretation of the

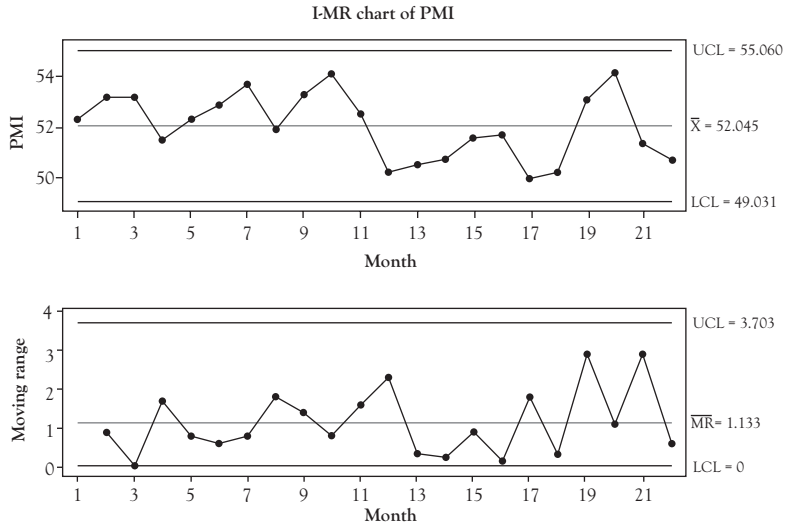


Figure 4.2 Individual and moving range (MR) charts for PMI data

Source: Created using Minitab 16.

charts in Figure 4.2 is different than what has been discussed previously. Since both the I-chart and MR chart are in control, the conclusion can be drawn that there have been no significant changes to the causal system underlying the PMI for the 22-month period plotted on the charts. But look what happens when we add the PMI data for the next four months as shown in Figure 4.3.

With the added data, we have a single point out-of-control signal on the MR chart at point 25, and single point out-of-control signals on the I-chart at points 23, 25, and 26. The very large increase in PMI from point 24 to point 25 is reflected in the out-of-control point on the MR chart. This signal indicates an increase in the variation of PMI from month to month and is very likely due to some change in the underlying causal system. The I-chart is out of control—abnormally low—at point 23 then returns to normal at point 24. At point 25 the I-chart is out of control—abnormally high—and remains out of control at point 26, indicating that whatever change occurred in the causal system at point 25 likely remains that way at point 26.

It is important to note that when a pair of charts is used to monitor the state of control of a process, an out-of-control signal on *either* chart

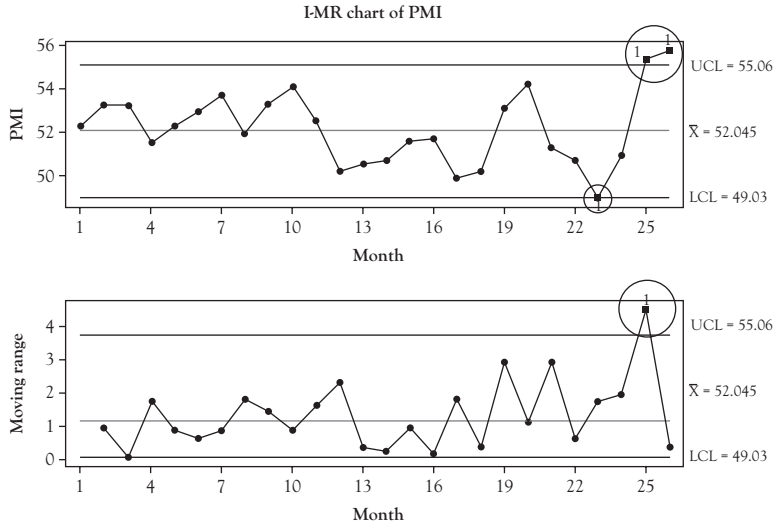


Figure 4.3 Individual and moving range charts for PMI data with additional data

Source: Created using Minitab 16.

indicates the statistical measure being plotted is out of control. This is more true for the x-bar and R and X-bar and s-charts, which will be discussed in the next section, than it is for the I- and MR-charts. This is because the points on the MR chart are correlated and many experts argue that the MR chart actually provides little useful information about changes in process variation.

X-Bar, Range, and Standard Deviation Control Charts

For many processes where the KQC is a variable, it is desirable to use samples consisting of two or more units instead of a single unit. Since the I-chart is designed to plot the data from a single unit, a new chart is required when using samples consisting of more than one unit. When this is the case, the control chart for means, called the x-bar chart (often shown as the $\bar{x}$ chart), is the right control chart for the job. x-bar ($\bar{x}$) is the symbol for sample mean, which is the statistic that is plotted on an x-bar chart. The x-bar chart is always used in conjunction with a control chart that monitors the variability of the KQC just as we needed the MR chart in addition to the I-chart. The range chart (referred to as the R-chart) is the

appropriate control chart for variation for sample sizes up to 10. For sample sizes greater than 10, it is necessary to use the standard deviation control chart (referred to as the s-chart) rather than the R-chart in conjunction with the x-bar chart. This is because with small sample sizes the range and standard deviation are almost the same, but as sample sizes become larger, the range diverges more and more from the standard deviation.

The points on an x-bar chart represent the means of each sample. The points on an R-chart represent the range within each sample. The points on an s-chart represent the standard deviation of each sample.

Figure 4.4 illustrates why it is important to use a control chart for variation (either an R-chart or an s-chart) in conjunction with the control chart for means (an x-bar chart). In Figure 4.4, the two dots represent the means of two samples plotted on an x-bar chart. The vertical lines coming from the data points represent the range of the data from which the means were calculated. The end of the top line from each point represents the largest individual value in the sample while the end of the bottom line represents the value of the smallest individual value in the sample. As you can see, both points are shown exactly the same on the x-bar chart—the sample means are equivalent—even though their ranges are quite different. Simply plotting a point on an x-bar chart is insufficient to capture this difference in the variation between the two samples. Indeed, based on the points alone, the process shown in Figure 4.4 appears to be in control because neither point is outside the control limits.

Figure 4.5 shows the information from the same sample as in Figure 4.4 plotted on x-bar and R-charts. The x-bar chart shows that the sample means are nearly unchanged while the R-chart clearly indicates a significant shift in the variability of the data between the two samples.

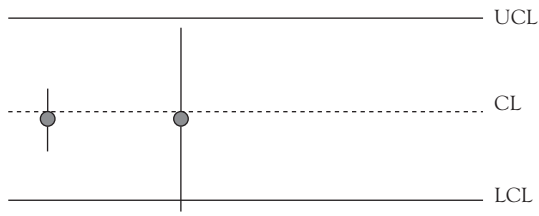


Figure 4.4 Why the x-bar control chart needs a companion range control chart for variation

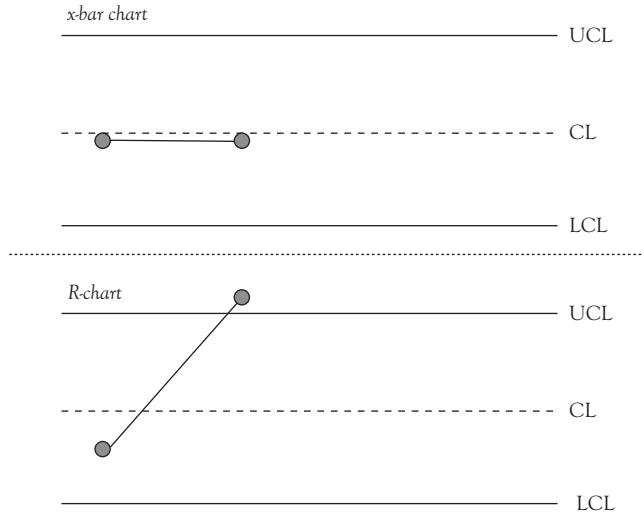


Figure 4.5 The x-bar control chart with its companion R control chart

When the sample size is greater than 10, the range is no longer a good measure of variation.[3] In this case, the standard deviation, or s-chart, is used instead of the R-chart. Figure 4.6 illustrates why it is important to use an s-chart in conjunction with the x-bar chart. The two dots represent the means of two samples plotted on an x-bar chart and the normal curves show the distribution of the data within each sample. As you can see, while the points representing the sample means are the same, the variability in their distributions is quite different. The variation in sample one is less than the variation in sample two. Simply plotting a point on an x-bar chart is insufficient to capture this difference in the variation between the two samples. Based on the x-bar chart alone, the process shown in Figure 4.6 appears to be in control because neither point is outside the control limits. When the s-chart is added, the process is shown to be out of control because the point representing the standard deviation for sample 2 is above the UCL.

When using x-bar and R- or s-charts, care must be taken in determining the sampling procedure. The following questions must be addressed:

- How frequently should the process be sampled? Sampling frequency is often a balance between efficiency and effectiveness. Too frequent sampling can be expensive and a wasteful

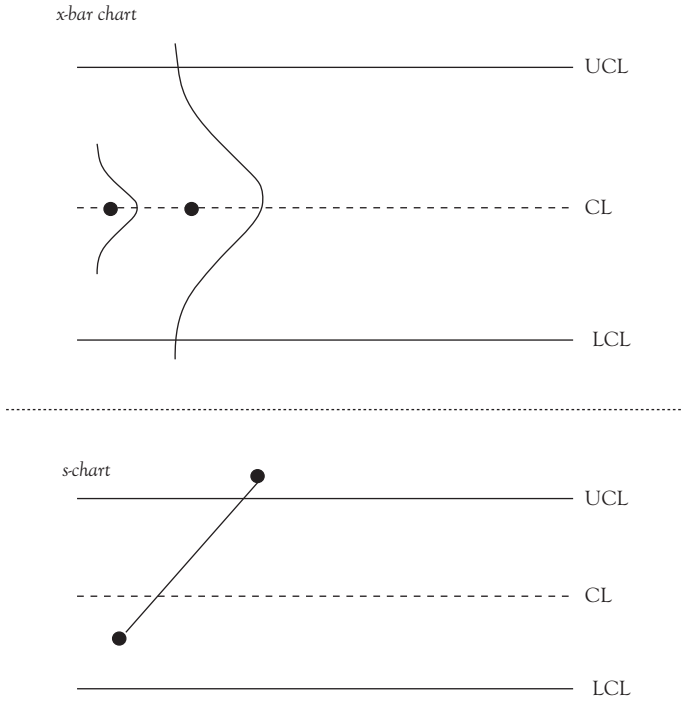


Figure 4.6 Why the x-bar control chart needs a companion standard deviation control chart for variation s-chart

use of resources. Samples taken at large intervals can allow an out-of-control condition to persist for too long.

- How large should the sample be? While in general, the larger the sample size the better, economics come into play. If the test is destructive, costly, or time-consuming, an economic sample size should be taken. In practice, sample sizes of 3 to 10 are commonly used.[4]
- How should units be selected for inclusion in the sample? Shewhart's rational subgroup concept is usually satisfied by taking consecutively produced samples for testing. Alternatively, random samples may be taken from all of the outputs of the process since the last sample was taken. Care must be taken to ensure that the samples represent a single process. Two machines that output units to a common conveyor, for

example, should be treated as separate processes with separate control charts. Sampling the combined output on the conveyor will lead to unreliable chart results. Samples should always be plotted on the control charts in time sequence order.

Example 4.1

x-bar and R-charts in Action

A manufacturer has instituted SPC for a process that produces approximately 5,000 units per 8-hour shift. The KQC being monitored is part weight and each measurement requires about 15 seconds. The sampling plan is used to select four consecutive units from the process about every two hours. The operator weighs each unit in the sample and immediately enters the data into Minitab 16, which plots the data on x-bar and R-charts. The operator has instructions to follow if an out of control condition is found. The data collected during the past 24-hour period are shown in Table 4.1.

Table 4.1 Part weights for units in 12 samples

Sample number	Unit 1 weight	Unit 2 weight	Unit 3 weight	Unit 4 weight
1	20.10	19.97	20.03	20.05
2	20.00	19.97	19.96	19.99
3	20.10	20.06	19.99	20.03
4	19.94	20.09	20.02	20.01
5	20.08	20.08	20.00	20.12
6	20.03	20.01	19.98	19.92
7	20.11	20.03	20.09	20.00
8	20.06	20.09	20.08	20.00
9	19.89	19.94	20.02	19.96
10	20.06	20.10	19.95	20.05
11	19.88	20.01	19.98	19.96
12	20.09	20.00	20.11	19.95

The x-bar and R-charts for these data are contained in Figure 4.7. The program creates the points to be plotted on the x-bar chart by calculating the average for each sample (20.0375 for sample 1 for example). The

points plotted on the range chart are ranges for each sample (0.13 for sample 1 for example). The control charts indicate that the process is in control.

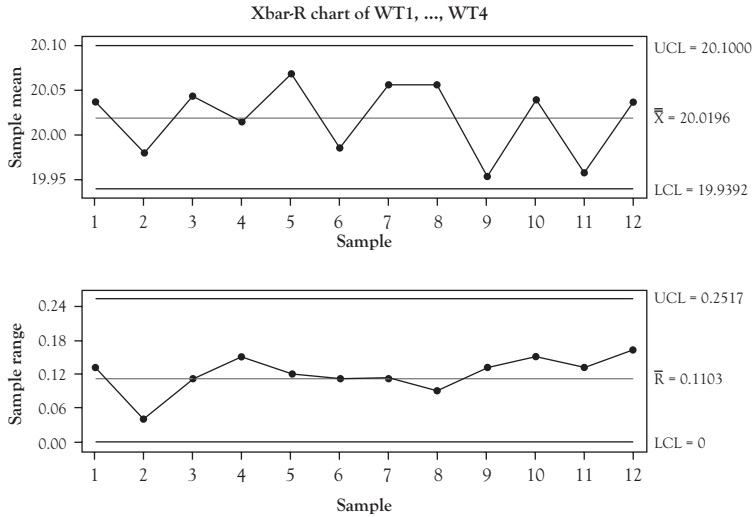


Figure 4.7 x-bar and R-charts for data in Table 4.1

Source: Created using Minitab 16.

Example 4.2

x-bar and s-charts in Action

If instead of taking samples consisting of four consecutive units as in Example 4.1, the organization decided to take samples consisting of 12 consecutive units, an s-chart should be used instead of an R-chart. The program creates the points to be plotted on the x-bar chart by calculating the average for each sample just as in Example 4.1. The points plotted on the s-chart are standard deviations for each sample. Figure 4.8 shows the x-bar and s-charts for this process. The control charts indicate that the process is out of control due to point 9 being below the LCL of the x-bar chart. The operator followed the instructions for reacting to an out-of-control signal, identified and corrected the root cause of the problem, and the next sample shows that the process has been brought back into a state of control.

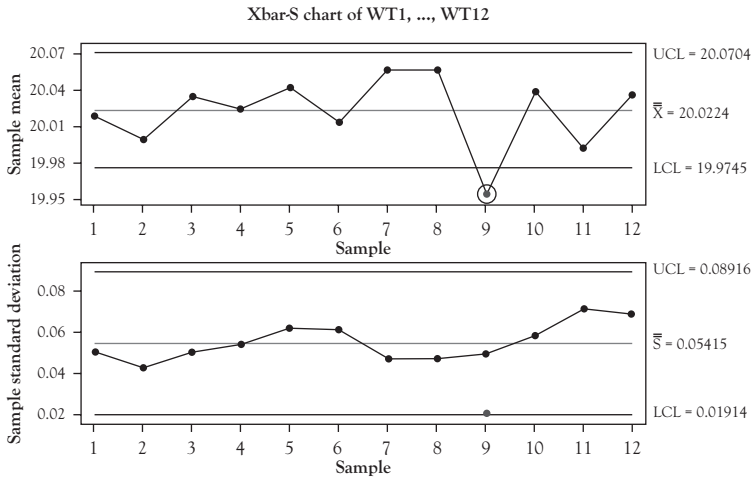


Figure 4.8 x-bar and s-charts for samples consisting of 12 units

Source: Created using Minitab 16.

When much of the science of SPC was being developed, computers and electronic calculators were not available for doing the calculations. For this reason, range charts were favored over standard deviation charts because of the extra complexity of calculating the points to be plotted on the s-chart. With the widespread availability of electronic calculators, computers, and reasonably priced SPC software, it is as easy to construct an s-chart as it is an R-chart. Since the range becomes less effective at showing the variation within a sample as sample size increases, it is best to use the s-chart than the R-chart when sample size is 11 or greater. The s-chart may also be used with sample sizes less than 11.

Chapter Take-Aways

Figure 4.9 provides guidance for selecting among the control charts discussed in this chapter.

- Variable data are continuous measurement information. Examples include measurements of height, weight, length, concentration, and pressure (psi).

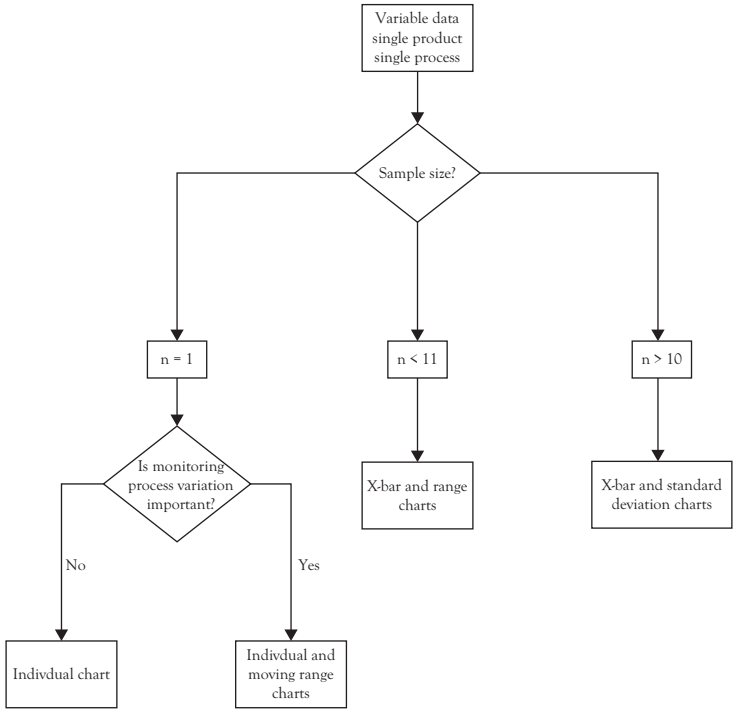


Figure 4.9 Basic variables control chart selection guide

- While I-charts are sometimes used alone, generally, variables control charts are employed in pairs. One chart monitors the changes in the process average (mean) while the other monitors changes in the process variation. The pairs of charts discussed in this chapter are the I- and MR charts, the x-bar and R-charts, and the x-bar and s-charts.
- The individuals chart alone is superior to a run chart because the control limits allow the user to determine when observed variation is significant. That is, the individuals chart allows the determination of the state of control of the process while the run chart does not.
- When using x-bar and R- or s-charts, care must be taken in determining the sampling procedure. The following questions must be addressed:
  - How frequently should the process be sampled?
  - How large should the sample be?
  - How should units be selected for inclusion in the sample?

- When using paired control charts, both charts must be in contol to conclude that the process is in control.

Questions You Should be Asking About Your Work Environment

- *Which processes have KQCs that are measured using variables data and are candidates for monitoring with variables control charts?*
- *For the processes identified by the previous question, what would be the value of monitoring those process using SPC?*

CHAPTER 5

Advanced Control Charts for Variables

If all you have is a hammer, everything looks like a nail.

—Abraham Maslow

While the control charts for variables discussed in Chapter 4 are sufficient to cover most situations, there are a number of additional control charts for variables that are better for certain applications. This chapter introduces new control charts for variables and adaptations of charts we have already discussed. Each expands the utility of control charts beyond that discussed in the previous chapter.

The Delta Control Chart for Short Production Runs

There are many situations where items are produced in small lots, which make the use of the variable control charts discussed in the previous chapter more difficult. With small lot sizes, there may be an insufficient number of samples per lot to use pattern rules—run rules, zone rules—to detect changes in the process over time. It is also more difficult to detect other nonrandom patterns due to shift changes, raw material lot changes, or operator changes. Modern mixed model production where a variety of parts from a common part family is produced *just-in-time* (JIT) make the traditional control charts for variables impossible to use. Figure 5.1 illustrates a production line where two different sizes (tall and short) of a product are produced JIT. The delta control chart[1] is designed for use in these short production run situations.

If a separate x-bar chart is used for each part produced by the process in Figure 5.1, the operator will constantly be switching from chart to chart to match the production mix. Often only a few points will be

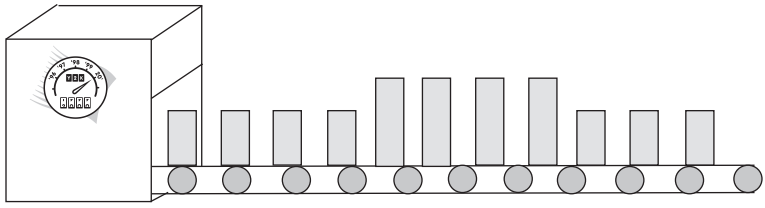


Figure 5.1 Mixed model production

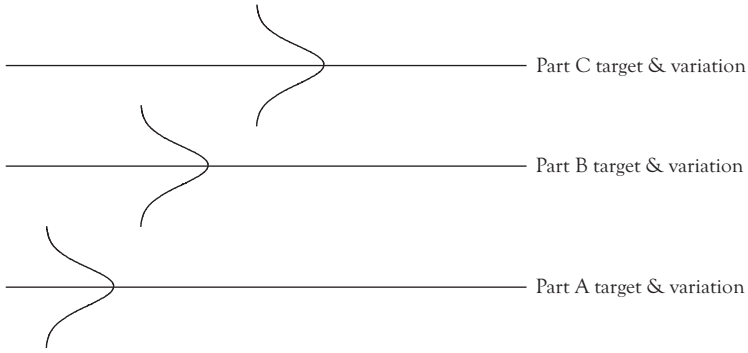


Figure 5.2 Equal variances but different targets

plotted on a chart before it is necessary to switch to a different one. But, as shown in Figure 5.2, given that the variation in the key quality characteristics (KQC) being monitored is not significantly different from part type to part type—and this should be tested—a single delta chart can be used for all of the parts produced by the process.

The delta control chart is known by a variety of names including the DNOM chart, the Nom-I-Nal chart, the deviation from nominal chart, and the code value chart. The delta chart functions in the same way as an x-bar chart and, as with the x-bar chart, is used in conjunction with an R- or s-chart. Because the target value of the KQC being plotted on the delta chart changes from small lot to small lot, the values used to calculate the sample mean to be plotted on the chart are the differences between the measured value and the target value. This is called the delta statistic.

The delta statistic is easily calculated using a spreadsheet such as Excel or within the SPC software used to create the control chart. Table 5.1 illustrates the calculation of the delta statistic where two parts per sample

Table 5.1 Calculation of the delta statistic

Sample No.	Part ID	Target	Observation 1 raw	Observation 1 delta	Observation 2 raw	Observation 2 delta	Delta-Bar
1	A	1.000	1.002	0.002	1.004	0.004	0.003
2	A	1.000	0.991	–0.009	1.009	0.009	0.000
3	B	1.500	1.497	–0.003	1.501	0.001	–0.001
4	B	1.500	1.501	0.001	1.503	0.003	0.002

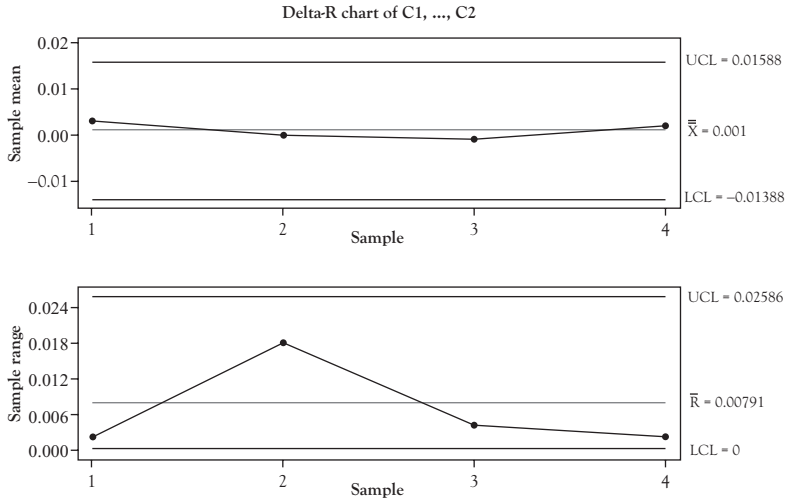


Figure 5.3 Delta and R-charts

Source: Created using Minitab 16.

are taken and where two different parts (A and B) are being produced by the same process. The raw data are entered into the software that calculates the delta statistic (Observation – Target). Delta-bar, which is the mean of the delta statistics for each sample [for example (0.002 + 0.004)/2 = 0.003 Delta-bar for Sample No. 1)], is plotted on the delta chart.

The delta chart, shown in Figure 5.3 with its companion R-chart, looks like the x-bar chart, but note that if all parts are, on average, exactly centered on the target value, the central line (CL) of the delta chart will be zero with the points evenly distributed on either side of the CL when the process is operating in control.

Example 5.1

Universal Machining

Universal Machining produces machine parts for the automotive industry. Their customer requires frequent shipments of small lots to be delivered to their production facilities. To accommodate their customer, Universal has implemented mixed model production. Mill #1 is dedicated to producing a particular part family that consists of six similar parts with slightly different dimensions. One of those dimensions is the KQC that is used to measure the quality of the finished part.

Recently Universal Machining implemented SPC and began using a separate x-bar and R-chart pair for each of the six parts produced on Mill #1. The early results of the use of SPC were disappointing. There had been shifts that occurred in the process that were not detected by the control charts because the run lengths of each part were too short. In addition, production supervisors were overheard complaining about the large number of control charts that required maintaining on the production floor. One commented that he felt he was producing control charts rather than product.

The quality engineer assisting in the SPC implementation decided to use Mill #1 as the pilot process for switching from x-bar and R-charts to delta and R-charts. Her first step was to collect sufficient data from the process to confirm that the variances in the KQC for the six parts produced on Mill #1 were not significantly different. That being confirmed, her next step was to gather sufficient data to construct the control charts and train the operators in the use of delta and R-charts.

The switch was a great success. Patterns that had gone unnoticed in the past were now evident in the delta chart. One new pattern indicated a shift to shift variation in the delta statistic, which was corrected through standardization of training for all of the mill's operators. The supervisors were encouraged at the reduction from six pairs of charts to a single pair of charts. The next step was to evaluate the suitability of using delta charts on other processes in the facility.

Exponentially Weighted Moving Average (EWMA) Chart

A variables control chart that is a good alternative to the I-chart is the exponentially weighted moving average (EWMA) chart, which is often used to detect small shifts in the process. The EWMA "is a statistic for monitoring the process that averages the data in a way that gives less and less weight to data as they are further removed in time"[2] and is much less sensitive to non-normality than the I-chart. The EWMA control chart "is useful for smoothing out short-term variance in order to detect longer term trends."[3] This smoothing effect makes the EWMA chart less sensitive to individual points that are unusually large or small.

The plotted data points on all of the previously discussed control charts are considered to be independent, and the decision made about the state of control of the process using the single point signal depends solely upon the last point plotted. The EWMA chart, however, uses an exponential weighting system, which makes each plotted point a function of the current observation plus some portion of previous observations.

The amount of weight given to previous points can be adjusted by selection of the weighting factor (α). When the weighting factor is set to one, no weight is given to prior points. As the value of the weighting factor is made smaller, the amount of weight given to previous points increases. Changing the weighting factor and the number of standard deviations to set the upper control limits and lower control limits enables the construction of an EWMA chart that can detect almost any size shift in the process.

While various sources recommend specific weighting factors, in practice it is important to make this determination based upon the data and what the organization is trying to accomplish by use of this chart. Smaller weighting factors increase the sensitivity of the chart to out of control signals, but also increase the number of false signals. Figure 5.4 shows two EWMA control charts both constructed with the PMI data used in Figure 4.3. Figure 5.4a uses a weighting factor of 0.10 while Figure 5.4b uses a weighting factor of 0.40. The charts are quite different from the I-chart in Figure 4.3 and quite different from each other which highlight the importance of the appropriate selection of the weighting factor when

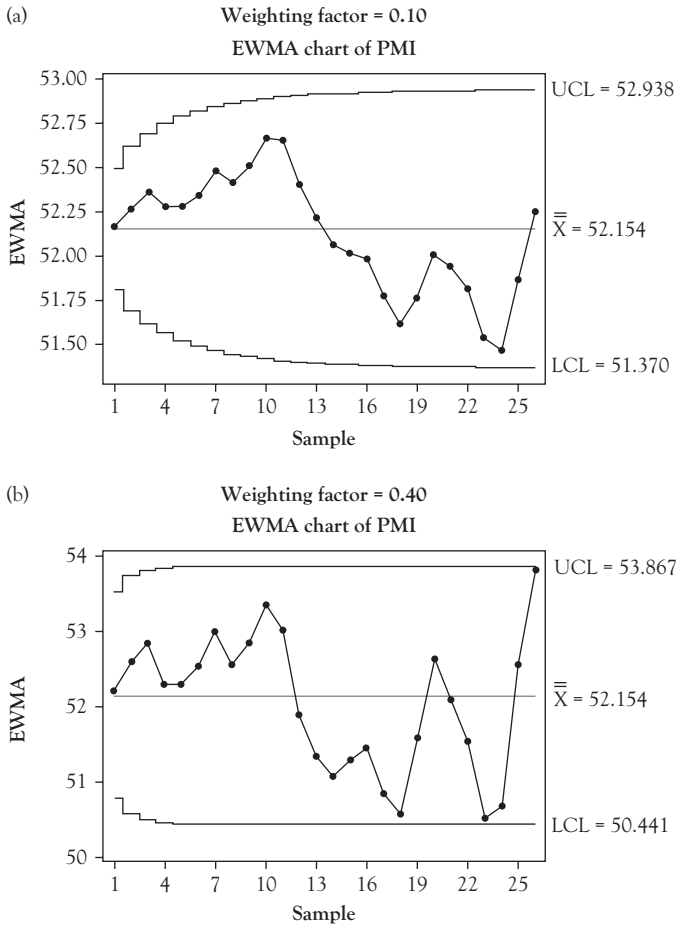


Figure 5.4 EWMA charts using the same data but different weighting factors

Source: Created using Minitab 16.

using EWMA charts. Weighting factor selection requires considerable skill. If sufficient skill is lacking in the organization, it is best to use I- and MR charts instead of the EWMA, because the utility of the EWMA chart is highly dependent on weighting factor selection. A naïve selection of the weighting factor is likely to result in misleading conclusions being drawn from the chart.

It is possible to use the EWMA control chart for sample sizes greater than one, but this application is beyond the scope of the current discussion.

Variables Control Charts with Unequal Sample Size

There are many situations where it is desirable or logical to work with data where the sample sizes are not equal. Examples include:

- Each day's production is considered to be a sample and each unit produced is tested. Production rates per day often vary.
- Measurement of a variable customer KQC where each day is considered to be a sample and the number of customers varies from day to day.
- Mixed model production where each unit is tested and lot sizes for each model vary.

The control chart applications discussed to this point apply to samples of the same size—that is, sample size does not vary. However, X-bar charts, R-charts, s-charts, and delta charts can be adapted to operate to situations where the sample size varies. When variable sample sizes are used, the control limits are adjusted for sample size for each point plotted on the control chart as shown in Figure 5.5.

The sizes of each of the 10 samples comprising the control chart in Figure 5.5 are shown in Table 5.2. The pattern of the adjustments is

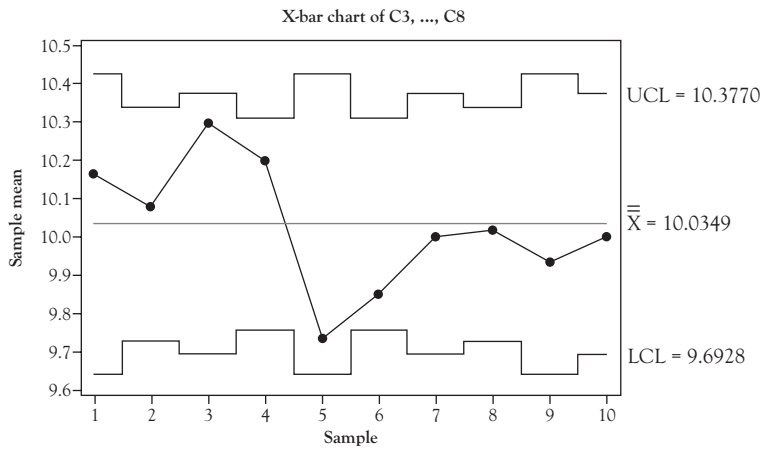


Figure 5.5 X-bar control chart with unequal sample size

Source: Created using Minitab 16.

Table 5.2 Sample sizes for control chart in Figure 5.5

Sample number	Sample size
1	3
2	5
3	4
4	6
5	3
6	6
7	4
8	5
9	3
10	4

clearly reflected in the variation in the sample sizes. When the sample size increases, the control limits are adjusted to be closer to the CL. When the sample size decreases, the control limits are adjusted to be farther from the CL. For example, the sample size for sample number 2 is larger than that for sample number 1. On the control chart that is reflected in the control limits for sample 2 being closer to the CL than those for sample 1.

Example 5.2

Variable Sample Sizes: A Service Example

A retailer of high-end merchandise is interested in tracking purchases by customers on a daily basis. The main purpose for the tracking is to provide an estimate of the effectiveness of advertising and promotions on purchase amounts per customer. The store manager plans also to track total daily sales as another measure of the effectiveness of advertising and promotions.

His first effort tracked daily sales and average sales per customer per day on run charts. He found that he was never sure whether the fluctuations he saw on the run charts were significant. His solution was to use SPC control charts instead of run charts. But which charts to use?

With the help of a professor at a local university, he examined the historical data and found that the daily sales data resembled a normal

distribution, but did not fit exactly. He explained to the professor that he was more interested in long-term trends than in short-term fluctations. The professor recommended an EWMA control chart.

The professor further explained that a pair of control charts for variables should be used to plot the daily purchases by customer. Each day would be defined as a sample, and the number of customers would be the sample size. One chart would be used to track the process mean. The x-bar chart with control limits adjusted for the varying sample sizes would be appropriate for this application. Since the number of customers was always much greater than 11, the s-chart, with control limits adjusted for sample size, would be appropriate for tracking the within sample variation.

This combination of control charts enabled the manager to better assess the effectiveness of advertising and promotions.

Chapter Take-Aways

Figure 5.6 provides guidance for selecting among the control charts discussed in this chapter.

Questions You Should be Asking About Your Work Environment

- *Which processes in your organization have defied attempts to use conventional control charts such as x-bar, range, and s-charts?*
- *Which of the processes identified in the previous question might be better suited for one of the control charts discussed in this chapter?*
- *What would be the value of monitoring those processes more effectively using a control chart specifically developed for those types of processes?*

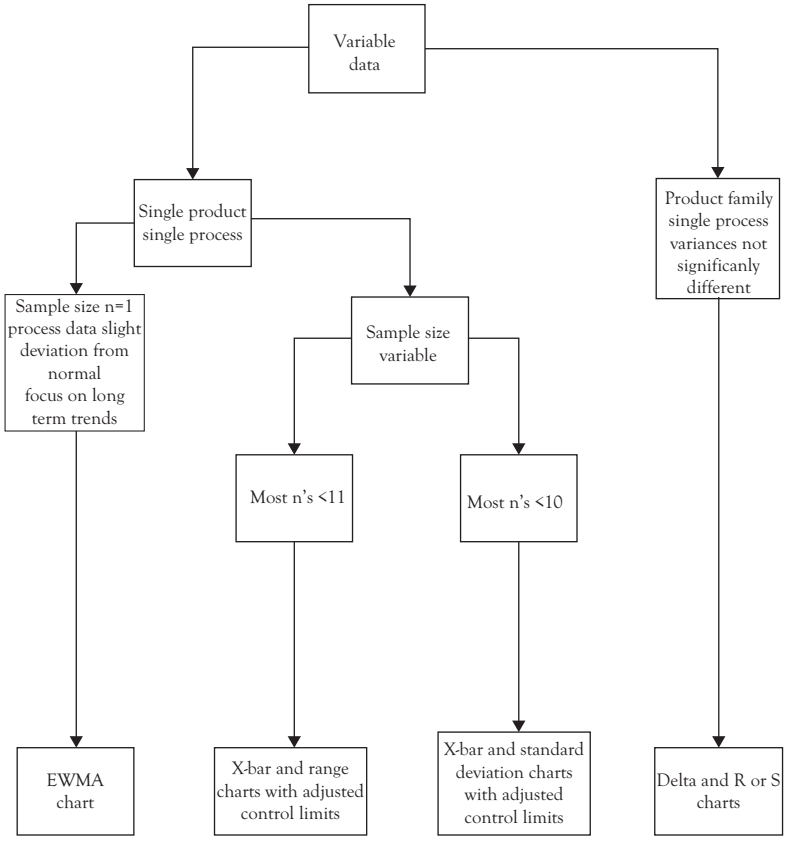


Figure 5.6 Variables control chart selection guide

CHAPTER 6

Control Charts for Attributes

Defects are not free. Somebody makes them, and gets paid for making them.
—W. Edwards Deming

The previous two chapters discussed control charts for variable data, which are continuous measurement information such as height, weight, length, concentration, and pressure. This chapter discusses control charts for attribute data that are go or no-go or count information. Examples include the number of defective units, the number of defects in a unit, the number of complaints received from dissatisfied customers, and the number of patients whose meals were delivered more than 15 minutes late. The theory supporting control charts for attributes is the same as has been discussed in Chapter 3. However, while the control chart for individuals used to illustrate that discussion is based on the normal distribution, control charts for attributes are based on different distributions. Signals that indicate an out-of-control condition are the same for both variables and attributes control charts.

All of the control charts in this chapter are for count data, but we must be sure to clearly define what we are counting in order to select the appropriate chart. The first two charts discussed in this chapter are for counting nonconforming or defective products. A defective or nonconforming product or service is one that cannot be sold or delivered as is because it does not meet the required specifications. Under this definition, a product exists in one of only two states: conforming or nonconforming (acceptable or defective).

The last two charts are for counting nonconformities or defects. A nonconformity is defined as the "nonfulfillment of a specified requirement," and similarly, a defect is defined as a "product's or service's nonfulfillment

of an intended requirement…"[1] A product may have a theoretically infinite number of defects. Whether the presence of defects renders the product nonconforming is determined by the specifications. For example, there may be a limit to the number of minor defects that are allowed in a product before it is rendered as nonconforming. The distinction between a defective (nonconforming) product and a defect (a nonconformity) is significant and is key to selecting the appropriate control chart for the job.

Proportion Defective Chart

The proportion defective control chart is also referred to as a percent chart, a fraction nonconforming chart, a fraction defective chart, or simply as a p-chart. ASQ defines a p-chart as a "control chart for evaluating the stability of a process in terms of the percentage (or proportion) of the total number of units in a sample in which an event of a given classification occurs."[2] Often the "event of a given classification" is whether the unit being examined is conforming (acceptable) or nonconforming (defective). The binomial distribution is the basis for the p-chart.

The p-chart is often used when large quantities of product are produced relatively quickly. For example, an injection molding process, which produces small parts with short cycle times in multiple cavity molds, would be a good candidate for a p-chart. One advantage of the use of p-charts is that multiple key quality characteristics (KQCs) can be combined using just one chart. When using control charts for variables, each KQC must have its own chart or pair of charts. The disadvantages of using p-charts compared to control charts for variables include the need for sample sizes significantly larger than with control charts for variables, and information about specific KQCs is not preserved on the p-chart as it would be on a control chart tracking a specific variable.

Example 6.1
p-charts in Action

An injection molding operation was producing a plastic boot that covers the end of an electronics cable. The parts were produced

automatically on a large molding machine using a 50-cavity mold with a short molding cycle. Many thousands of these parts were produced during each hour of production. There are a number of attributes that must be inspected for. A problem with any one attribute renders the part nonconforming. Typically, the company considered each shift's production to be a lot and evaluated each lot using an acceptance sampling plan. The major disadvantage of this plan is that problems that occur early in a shift are not detected until well into the next shift. Since a rejected lot must be inspected 100 percent (which was considered to be rework), considerable extra cost can be incurred as a result of failing to identify a problem as early as possible.

This process was chosen as the organization's pilot study for the implementation of statistical process control (SPC). The implementation team decided to sample the process four times per shift using a sample size of 200 with immediate inspection of the sample units. The results of the inspection would be recorded on a p-chart. The expectations for this SPC implementation were:

- Quicker recognition of process problems so that corrective can be taken more quickly with the result of fewer defective parts produced.
- A savings in inspection costs since the SPC sampling plan would require the inspection of 800 units per shift compared with the 1250 units per shift under the acceptance sampling plan.
- A savings in rework costs since the number of units subject to 100 percent inspection if a process problem is found would be about one quarter as many as with the acceptance sampling plan. This is because in this case we sample the output four times as often using SPC as with acceptance sampling so the number of items produced before a problem is detected is one-fourth as many as with acceptance sampling.
- Reduced product variation, which should manifest as better quality as perceived by the customer.

The implementation team made sure that the process was set up as designed and took 25 samples over the course of three shifts of

production. They used the data from these samples to construct the trial control chart shown in Figure 6.1. The process was shown to be in control and SPC was instituted as the standard operating procedure (SOP) for this process using the control limits established during the trial period. About two months later, the implementation team revisited the process and found that SPC was working as designed and that all expectations were being achieved.

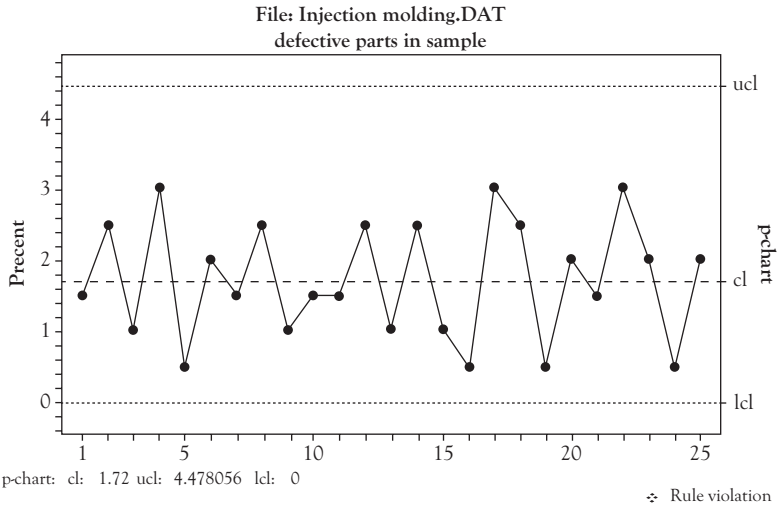


Figure 6.1 Trial p-chart

Source: Created using NWA Quality Analyst 6.3.

Notice that the distance between the central line (CL) and upper control limit (UCL) in Figure 6.1 is greater than that between the CL and lower control limit (LCL). This is because the LCL cannot always be set at three standard deviations below the CL because that would result in a negative proportion defective, which is impossible. In this case, the LCL is set at the lowest level that is possible, which is zero.

P-charts can be used with both fixed and variable sample sizes. Figure 6.1 illustrates an example using fixed sample size. However, there are many instances where sample size will vary—particularly in the service and healthcare sectors, which will be more specifically discussed in Chapter 8. Whenever the sample consists of all the items produced during a

period of time, it is likely that the sample size will vary. Even an automated manufacturing process that produces relatively constant amounts of product per day, all of which is subject to 100 percent automated inspection, is subject to variation in the sampling intervals, which creates a situation where sample size will vary. When the sample size varies, the control limits are adjusted for each sample, which explains why the UCL and LCL in Figure 6.2 are not straight lines but appear to have steps.

Example 6.2

p-chart for Varying Sample Size Leads to Improvement Project

A manufacturing company uses an automated system to apply labels to its products. Each labeled product is inspected using a pixel camera system, which detects any missing, crooked, or torn labels and removes the mislabeled product from the process flow. The inspection system automatically logs the number of units inspected and the number of units rejected. This allows the calculation of the proportion of the units inspected that are nonconforming. These data are plotted hourly on a p-chart. Since the number of units inspected per hour varies, the control limits for the control chart must be adjusted based on the sample size as shown in Figure 6.2. The control chart shows that the process is out of control because sample 25 is above the UCL.

The first action the company took was to determine the root cause for the out-of-control point. They then took appropriate corrective action, followed by taking a new sample to verify that the corrective action brought the process back into control.

The company also periodically reviews the control chart to determine how well the process is meeting expectations. The CL on this control chart is 0.05251, indicating that more than 5 percent of the labeled units are nonconforming. The organization in this case was not satisfied with this level of nonconforming product and initiated a planned improvement project with the goal of reducing the mean number of nonconforming labels produced by the process.

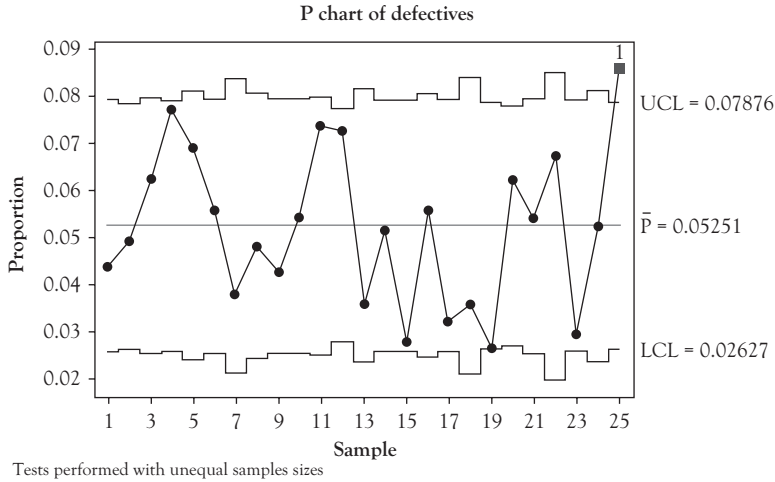


Figure 6.2 p-chart for labeling operation proportion defective per hour

Source: Created using Minitab 16.

Number-Defective Chart

The number-defective control chart is also referred to as an np-chart. The np-chart is an alternative to the p-chart. Adapting the definition of the p-chart, the np-chart is a control chart for evaluating the stability of a process in terms of the *number* of the total number of units in a sample in which an event of a given classification occurs. As with the p-chart, often the "event of a given classification" is whether the unit being examined is conforming (acceptable) or nonconforming (defective). Since the np-chart uses the number rather than the proportion of nonconforming units in each sample, sample size must remain constant. The binomial distribution is the basis for the np-chart.

As with the p-chart, the np-chart is often used when large quantities of product are produced relatively quickly and provides the same advantages and disadvantages as the p-chart. The main advantage of the np-chart over the p-chart is ease of understanding. Since the number of nonconforming units per sample is plotted on the chart, it provides direct evidence for the amount of nonconforming product being produced in units. Line operators often find units easier to understand than

proportions. A disadvantage of the np-chart compared to the p-chart is the inability to handle variable sample sizes.

The bottom part of Figure 6.3 shows an np-chart using the same data used to create the p-chart in Figure 6.1. The p-chart from Figure 6.1 is reproduced on the top to provide a comparison. The patterns in the charts are identical and both have equal power to respond to out of control conditions in the process.

Both the p- and np-charts are based on defective or nonconforming units—that is, units that are judged not to be in conformance with

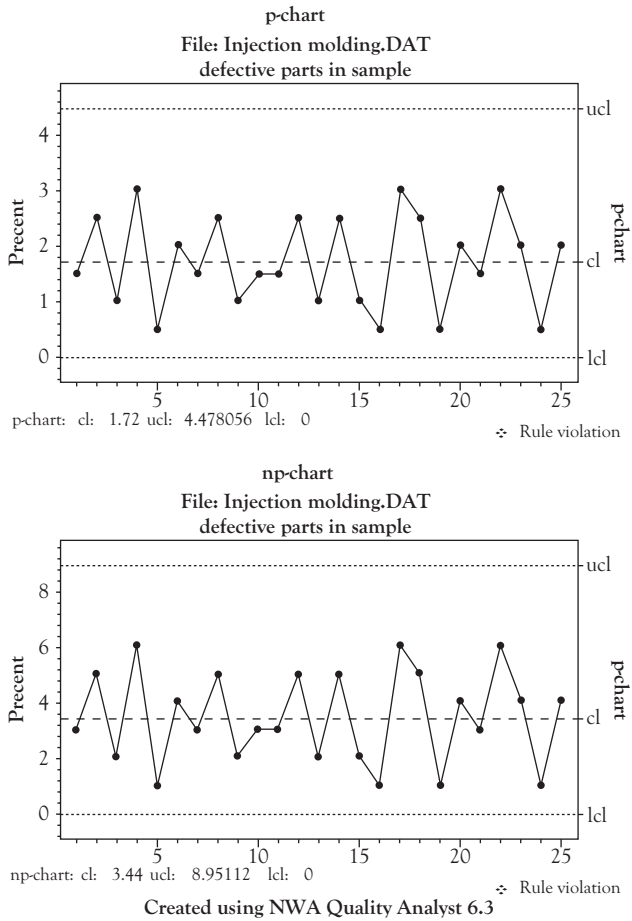


Figure 6.3 Trial p- and np-charts using the same data

Source: Created using NWA Quality Analyst 6.3.

specifications. The next set of charts, the c-chart and u-chart, are based on the number of nonconformities or defects found in a unit.

Count Chart or Number of Nonconformities in a Fixed-Size Sample

The count chart, also known as a number of nonconformities chart, is a "control chart for evaluating the stability of a process in terms of the count of events of a given classification occurring in a sample, and is known as a *c-chart*."[3] The events are generally nonconformities or defects. When using the p-chart or np-chart we are unconcerned with how many defects are present in a sample, just that for whatever reason or reasons, some units in that sample are considered to be nonconforming. In the case of c-charts we are concerned only with the number of defects that are present in a sample and not with how many nonconforming units are present. When using c-charts, the sample size should be constant. The Poisson distribution is the basis for the c-chart.

Consider the final inspection of the finish of an automobile. If the specification allows a specified number of minor defects in the finish, then until that limit is reached, the automobile being inspected is considered to be conforming even though some number of nonconformities is present. A p-chart or np-chart would fail to capture the information about the minor defects present in the finish. That is why the c-chart is appropriate in this case.

Example 6.3

The np-chart versus the c-chart

Each automobile moving off the end of the assembly line is hand inspected for minor defects in the paint finish. The specification allows a maximum of eight minor defects per automobile. More than eight minor defects render the automotive finish nonconforming or defective. The results of recent inspections are shown in Table 6.1.

Note that while there is a clear trend of increasing numbers of defects in the samples over time, none of the samples would be considered to be nonconforming until the 10th sample. When plotted on an np-chart, samples 1 through 9 would plot as zero defectives, indicating no significant variation in the process. In fact, the process appears to be absolutely stable with zero defective paint finishes until point 10. Clearly the np-chart does not accurately depict the real state of control of the process.

Table 6.1 Inspection record for automotive finishes

Sample number	Number of defects
1	0
2	1
3	2
4	3
5	4
6	5
7	6
8	7
9	8
10	9

The correct control chart to use in this situation is the c-chart. The c-chart, shown in Figure 6.4 shows that the process is out of control at point 8 using the "8 points in a row on a rising trend" run rule. The c-chart clearly shows that the process is deteriorating over time. The out-of-control signal at point 8 is received before we exceed the specification limit of eight minor defects, which provides time to investigate and correct the problem before we have produced a defective finish. While this is a contrived example, it clearly illustrates the importance of selecting the correct control chart for the job. When counting nonconformities (defects) in samples of fixed size, the c-chart is the correct control chart to use.

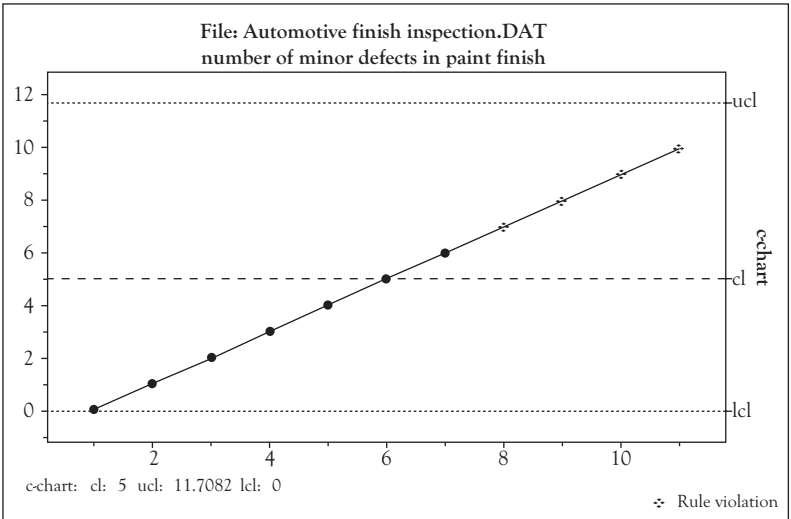


Figure 6.4 Automotive paint finish inspection c-chart

Source: Created using NWA Quality Analyst 6.3.

Count Chart for Nonconformities per Unit Where Sample Size May Vary

The count chart per unit, called a u-chart, is an adaptation of the c-chart that evaluates the stability of a process in terms of the count of events of a given classification occurring *per unit* in a sample. Unlike the c-chart, which uses fixed-size samples, the u-chart allows for the use of variable size samples. As with the c-chart, the events are generally nonconformities or defects. And as with the c-chart, when using a u-chart we are concerned only with the number of defects that are present in a sample and not with how many nonconforming units are present. The Poisson distribution is the basis for the u-chart.

There are many situations where the sample size varies. Many service applications involve variable sample sizes and will be discussed in more detail in Chapter 8. In manufacturing, when the entire population is inspected rather than samples taken from the population, sample size often varies. The u-chart handles this by calculating and plotting

the number of defects per unit and adjusts the UCL and LCL for the sample size.

Example 6.4

The u-Chart in Action

The manufacturer of coated polyester film uses an automatic inspection process to identify defects in the coating. The specific location of these defects is automatically recorded so that the manufacturer knows exactly where within the run the defects are located. Each hour, the number of defects is recorded along with the length of the coated product produced in linear feet. Data for 16 hours of production are contained in Table 6.2.

Table 6.2 Inspection record for coating defects

Sample number	Number of defects	Linear feet produced
1	27	9,250
2	17	8,100
3	16	8,500
4	24	8,900
5	22	8,650
6	28	9,040
7	19	8,750
8	26	9,100
9	24	9,200
10	21	8,850
11	25	7,250
12	19	8,850
13	20	8,750
14	26	8,950
15	28	8,800
16	19	9,100

Since we are tracking defects and sample size varies, the correct control chart to use in this situation is the u-chart. The u-chart, shown in Figure 6.5, indicates that the process is in control. Notice that the UCL and LCL vary as a result of adjustments due to variations in sample size. When counting nonconformities (defects) in samples of variable size, the u-chart is the correct control chart to use.

The manufacturer was not happy with the level of defects in the coated rolls. The CL on the u-chart is 0.002577835, indicating that there are approximately 0.00258 defects per linear foot. Based on the information on the u-chart in Figure 6.5, the manufacturer recognized that the process was in control—operating as currently designed. So a project to improve the process was initiated with a goal of reducing the number of defects per linear foot by 25 percent within three months.

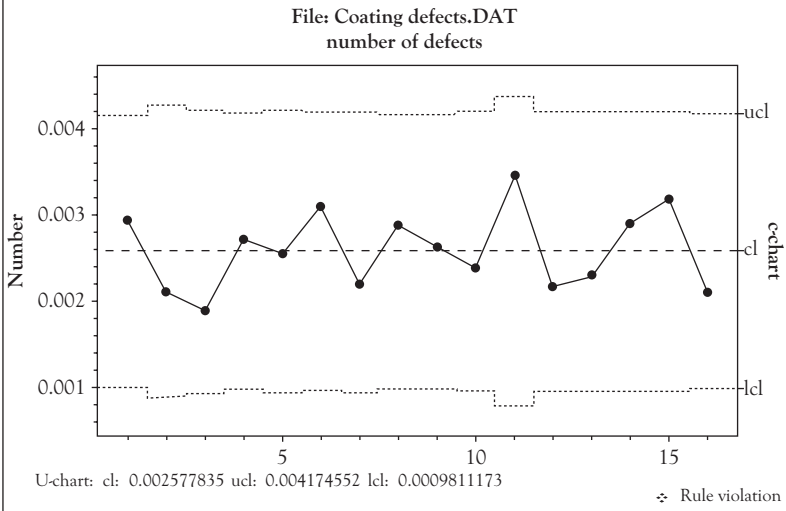


Figure 6.5 Coating defect u-chart

Source: Created using NWA Quality Analyst 6.3.

Chapter Take-Aways

Figure 6.6 provides guidance for selecting among the control charts discussed in this chapter.

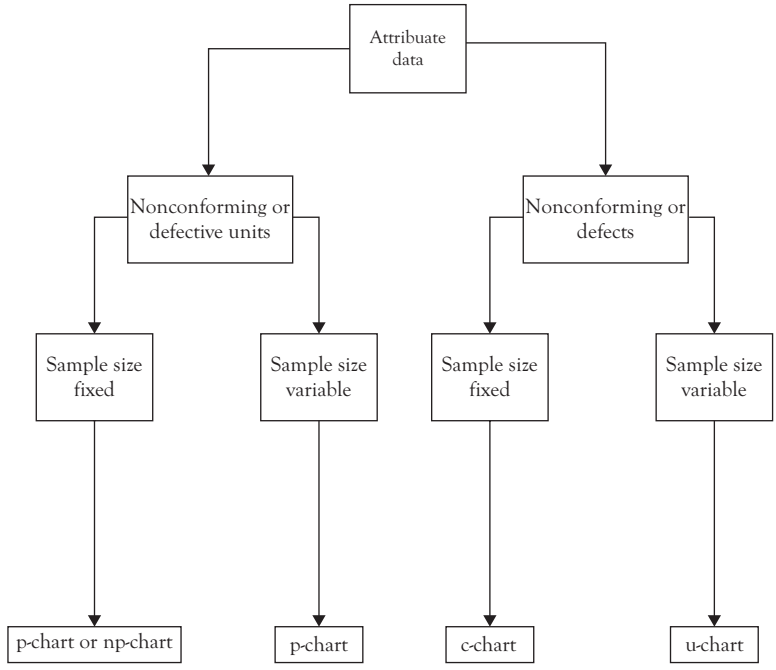


Figure 6.6 Attribute control chart selection guide

Questions You Should Be Asking About Your Work Environment

- *Which processes have KQCs that are measured using attribute data and are candidates for monitoring with attribute control charts?*
- *For the processes identified by the previous question, what would be the value of monitoring those process using SPC?*
- *What data that are monitored by your organization might have greater value for decision-making purposes if tracked using an attribute control chart?*

CHAPTER 7

Process Capability

Our work is the presentation of our capabilities.

—Edward Gibbon

The debate over the true definition of quality is as strong as ever with no resolution in sight.[1] For the purposes of our discussion of process capability, we will use a definition based on Juran's fitness for use and Feigenbaum's best for certain customer conditions.[2] Edward Lawson built on Juran's and Feigenbaum's work when he crafted his definition of quality as "the degree of excellence with which a product or service fulfills its intended purpose."[3] The intended purpose is defined by the marketplace, according to Lawson, and the intended purpose is translated into specifications that manufacturers use to assure the products they produce meet the customers' intended purpose—that is, they are of good quality. As John Guaspari put it, "Customers aren't interested in our specs. They're interested in the answer to one simple question, "Did the product do what I expected it to do?"[4]

Process capability assesses how well the process, when operating in control, is able to meet the specifications. Process capability is important because simply being in control is not sufficient. A process that consistently produces nonconforming product can still be in control. Figure 7.1 illustrates a process operating in control with little variation but that fails to produce products that meet specifications because the process is not centered on the specification.

Figure 7.2 illustrates a process operating in control and that is centered on the specification that produces considerable amounts of nonconforming material because the process limits are too wide—that is, there is too much variation. While the control charts (not shown) for both illustrated processes indicate they are in control, neither of the processes

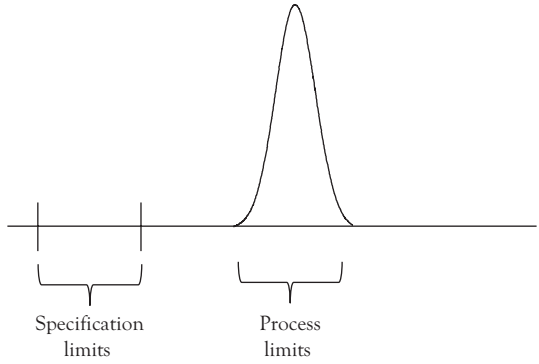


Figure 7.1 In control, but not capable (A)

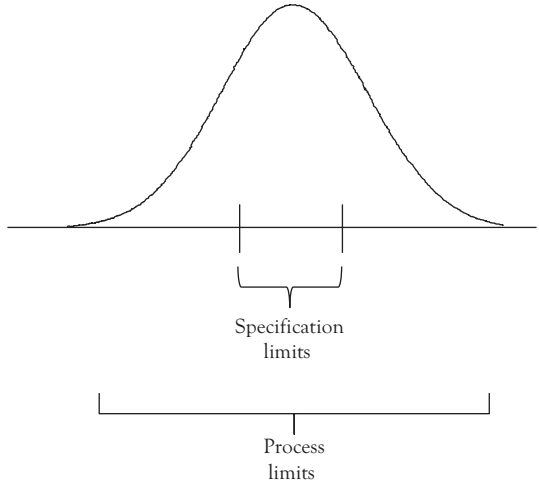


Figure 7.2 In control, but not capable (B)

shown in Figures 7.1 and 7.2 are capable since so much of the distribution is outside the specification limits. What is desired is a process that is *both* in control and capable.

Measurement of process capability differs for variable and attribute data. For that reason, we will deal with each separately.

Process Capability for Variable Data

There are several ways to measure process capability for variable data that we will discuss in this chapter. Among these are the process capabil-

ity indices C_p, C_{pk}, and C_{pm}. These indices compare specifications for a product (what you desire the process to produce) to the process's performance capability (what the process can achieve when operating in control). Regardless of which of these statistical indices is used, the first step in assessing process capability is to confirm that the specifications accurately reflect the customers' intended purpose. The second step is to confirm that the process is in control. The third step is to compare the variation of the in-control process to the spread of the specifications using some form of an index.

When the process is not in control, some experts recommend using the indices P_p and P_{pk} (known as process performance indices) to obtain an initial measure of process capability before the process is brought into a state of statistical control. However, if the process is not in control, these indices have no predictive capability because the process is not predictable. Indeed many experts[5] regard the use of P_p and P_{pk} as a "step backward in quantifying process capability." One expert[6] flatly states that P_p and P_{pk} "are a waste of engineering and management effort—they tell you nothing." Therefore, it is recommended that the process first be brought into a state of control, then use C_p, C_{pk}, or C_{pm} as measures of process capability rather than using P_p or P_{pk}.

Because all of these indices are a ratio of the spread of the specifications (distance between the upper and lower specification limits) and the variation in the process ($\pm 3\sigma_x$), it is obvious that only two actions can increase the value of the ratio: increase the spread of the specifications or decrease the process variation.

The higher the value of the index the more capable is the process. Standards for considering a process to be capable sometimes differ from industry to industry and organization to organization. A general rule is that a C_p index value of 1.33 is a minimum acceptable standard for capability. As Table 7.1 shows, this corresponds to 63 parts per million defective (ppmd), assuming a perfectly normal distribution, which is a 4 sigma level of quality (See Table 7.1 footnote). In this context, 4 sigma refers to the upper specification limit (USL) and lower specification limit (LSL) coinciding with ± 4 standard deviations from the process mean—a total spread of 8 standard deviations. The larger the value of the capability ratio, the larger the magnitude of an assignable cause event that can be tolerated without generating large amounts of out-of-specification material.

Table 7.1 C_p and ppm defective

Quality level	C_p	ppm defective
3 sigma	1.00	2,700
4 sigma	1.33	63
5 sigma	1.67	0.57
6 sigma*	2.00	0.002

Source: Sower (2011); Adapted from Tadikamalla (1994).

**The* Six Sigma quality program allows the distribution mean to drift by ± 1.5 standard deviations. Six sigma quality without the drift equates to 0.002 ppm defective. Six Sigma quality with the drift allowed equates to the often quoted 3.4 ppm defective or 3.4 defective parts per million opportunities.

When the process is centered on the target value of the specification (T), there are only two actions that can be taken to improve process capability as shown in Figure 7.3:

- Decrease process variation
- Loosen the specification

If the process is not centered on the process specification, process capability can also be improved by centering the process on the specification (see Figure 7.6).

The equations for calculating the measures of process capability discussed in this section may be found in Table A.4 in Appendix A.

Example 7.1

Why Isn't C_p = 1.00 Good Enough?

A manufacturer of electronic toys aspired for a process that is in control with a C_p of 1.00. "After all, we're not producing space shuttles. I don't think that 2,700 defective toys out of every million produced is so bad. That is only about 1 defective product out of every 400 units produced, which means that 99.73 percent or our products work properly. We will just replace the defective ones that are returned by the customer."

But assume that her toys are comprised of 100 components each produced by processes that are in control and have a C_p = 1.00. If any one of these components fails to work properly, the toy will fail

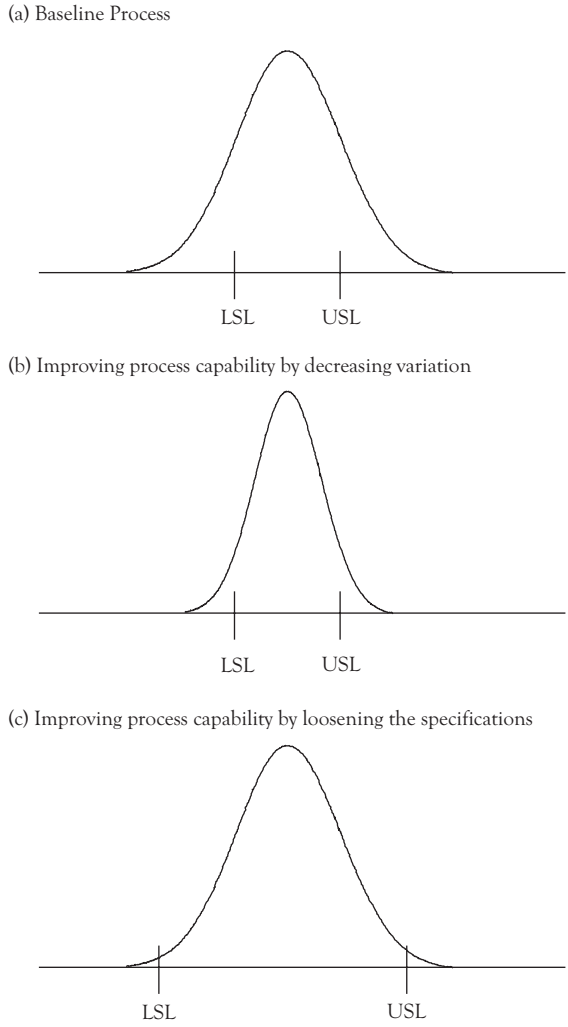


Figure 7.3 Improving process capability

to work. Each component has a probability of working properly of 0.9973. The probability of all of the components working properly is 0.9973 × 0.9973 × 0.9973 … 100 times or 0.9973^{100}. The resulting reliability is 0.7631. That means that about 24 out of each 100 products produced will be defective. This is hardly acceptable even for toys. A higher standard is needed. At the minimum accepted standard $C_p = 1.33$, the reliability of the toy would still be just 0.8591, resulting in about 14 defective toys per 100 produced.

C_p

C_p is defined by ASQ as the "ratio of tolerance to 6 sigma, or the USL minus the LSL divided by 6 sigma. It is sometimes referred to as the engineering tolerance divided by the natural tolerance."[7] This definition uses the term tolerance while this book uses the term specification to mean the same thing. Note also that in this definition, 6 sigma refers to a total spread of 6 standard deviations—3 standard deviations below the mean plus 3 standard deviations above the mean. This does not have the same meaning as Six Sigma referring to the quality program used by some organizations to reduce process variation.

C_p is an appropriate measure of process capability when:

- The specification is two sided—that is it has both an upper and a lower bound.
- The process is centered on the specification target value (see Figure 7.2).
- The individual measurements of process output are approximately normally distributed.
- The process is in control.

Statistical process control (SPC) uses statistics derived from both samples and individuals. It is important to understand when to use each. This is especially true when dealing with x-bar charts and process capability analysis. Data are collected for the construction of x-bar charts using rational subgroups (see Chapter 4) or samples consisting of two or more observations. The sample means ($\bar{x}$) are calculated along with the sample ranges (R) or sample standard deviations (s). The mean of the sample means is the grand mean ($\bar{\bar{x}}$), the mean of the sample ranges is $\overline{R}$, and the standard deviation of the sample means is $\sigma_{\bar{x}}$. These statistics are used to determine the UCL and LCL for the x-bar chart upon which the sample means are plotted.

Usually these same data are used to determine a measure of process capability such as C_p or C_{pk}, but for process capability purposes, it is the individual measurements rather than the sample statistics that are used. For more detail about this topic, see Appendix A.

Example 7.2

Using the Same Data for an X-Bar Chart and Process Capability

Part weight data were collected from a molding operation for the purpose of implementing SPC for the process. Twenty-five samples consisting of four parts each were collected from the process as shown in Table 7.2.

Table 7.2 Sample data

Sample no.	Part 1	Part 2	Part 3	Part 4
1	19.97	20.03	20.05	20.10
2	19.97	19.96	19.99	20.00
3	20.06	19.99	20.03	20.10
4	20.00	20.02	20.01	19.94
5	20.08	20.00	19.84	20.08
6	20.01	19.98	19.92	20.03
7	20.03	20.06	20.00	19.98
8	20.03	20.02	20.00	20.08
9	19.94	20.02	19.96	19.89
10	19.92	19.95	20.05	20.06
11	20.01	19.98	20.02	19.88
12	19.90	20.00	19.95	20.09
13	19.97	20.03	20.05	20.10
14	19.97	19.96	19.99	20.00
15	20.06	19.99	20.03	19.92
16	20.03	20.02	20.01	19.94
17	20.08	20.00	20.08	20.08
18	20.01	19.98	19.92	20.03
19	20.03	20.00	20.00	19.94
20	20.03	20.04	20.00	19.94
21	19.94	20.02	19.96	19.89
22	19.98	19.95	20.02	20.06
23	20.01	19.98	19.96	20.06
24	20.00	20.11	19.95	20.09
25	19.97	19.98	19.99	20.00

First, the sample means and sample ranges were calculated by the SPC software package and used to construct x-bar and R-charts. Figure 7.4a shows that the process is in control. Next, the individual observations were analyzed and the process mean and standard deviation were calculated and used to analyze process capability. Figure 7.4b shows that the process distribution is approximately normal and reasonably centered on the specification target. The organization uses a standard of C_p at or above 1.33 to classify a process as being capable. Using this standard, the process is capable since Figure 7.4b indicates C_p is 1.5458.

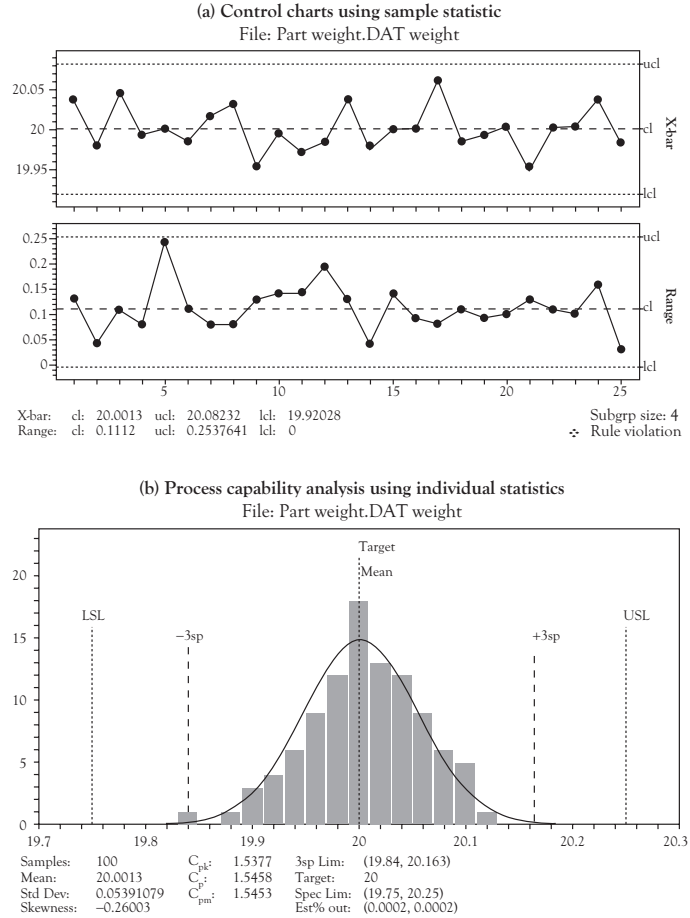


Figure 7.4 State of control and capability analysis using data in Table 7.2

Source: Created using NWA Quality Analyst 6.3.

Figure 7.4b shows a typical process capability report. From this report, we can see that the process distribution is approximately normal and the process mean almost exactly coincides with the target value of the specification. On the printout, samples = 100 indicates that 4 observations from each of the 25 samples were used in this analysis (4 observations per sample × 25 samples = 100 individual observations). Three process capability indices are reported: C_p, C_{pk}, and C_{pm}. The final entry on the printout (Est. out) shows that over time, approximately 0.0002 percent of the process output is expected to fall below the LSL and 0.0002 percent is expected to fall above the USL for a total prediction of a long-term average of 0.0004 percent of the output failing to meet specifications.

C_{pk}

When the second requirement for using C_p, "the process mean is centered on the specification target" (see Figure 7.1), is not met, then the proper index to use is C_{pk}. Think of C_{pk} imposing a penalty on process capability if the process is not centered on the specification target value. C_{pk} examines the distance between the USL and the process mean and the distance between the LSL and the process mean. It calculates two ratios: (1) the ratio of distance between the process mean and the LSL to 3 sigma and (2) the ratio of the distance between the USL and the process mean to 3 sigma. The former ratio is referred to as C_{pl} and the latter as C_{pu}. C_{pk} is the minimum of these two ratios.

Figure 7.5 illustrates a situation where the specification target value is higher than the process mean (μ). The distance between the LSL and the process mean is smaller than the distance between the process mean and the USL. Since each distance is divided by the same value, 3 sigma, that means C_{pl} will be smaller than C_{pu} and C_{pk} would be set at the value of the C_{pl}. As with C_p, the higher the value of the C_{pk} the more capable is the process. The general rule is that a C_{pk} value of 1.33 is a minimum acceptable standard for capability although many organizations adopt a different value of the index for their purposes.

When the process is perfectly centered on the specification target value, C_p and C_{pk} will be identical. For un-centered processes, centering the process on the specification target value will increase process

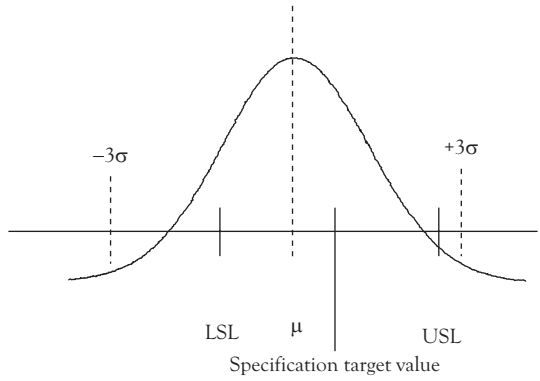


Figure 7.5 C_{pk}, C_{pl}, *and* C_{pu}*—Process not centered on target value*

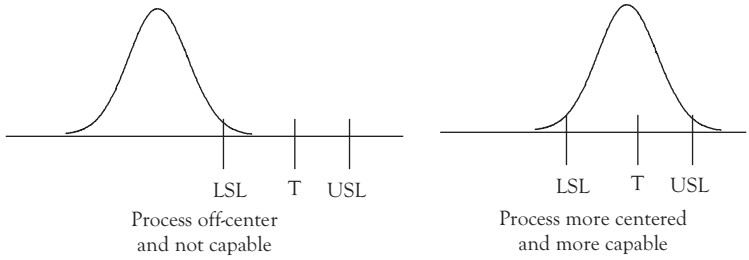


Figure 7.6 Process improvement through shifting of the mean

capability. Note in the process capability printout in Figure 7.4b, the process is not exactly centered on the process mean. We can tell that because C_p is 1.5458 while C_{pk} is 1.5377—close but not identical. We would use C_{pk} as the current capability of this process while the difference between C_p and C_{pk} represents the amount of improvement that could be achieved by perfectly centering the process on the target value. Often shifting the process mean to more closely align with the specification target value is easier to accomplish than reducing process variation. For this reason, shifting the mean so that it more closely coincides with the specification target value should not be overlooked as a possible source of process improvement as shown in Figure 7.6.

C_{pm}

C_{pk} exacts a penalty for the process not being centered on the specification target value, but the value of this penalty is small if the process variation

is small enough so that the amount of out-of-specification product produced is small. C_{pm} is an index that is based on the Taguchi loss function, which, in part, states that there is a loss to society when a process mean is off target (ideal value) even if no out-of-specification product is produced.[8,9] Some consider C_{pm} to be the best overall "indicator of how your customers experience the quality of your product or service."[10]

While C_p and C_{pk} use the process mean when calculating the spread of the observations, C_{pm} uses the specification target value instead and compares this spread with the distance between the USL and LSL. In the left-hand illustration in Figure 7.6, the process is so far off target that it is obvious that significant amounts of out-of-specification product will be produced. C_{pk} penalizes for this. Figure 7.7 illustrates the situation where the process is not centered, but the variation is small enough that little out-of-specification product is produced. C_{pm} penalizes more than C_{pk} in this situation. Most SPC software reports C_{pm} as well as C_p and C_{pk} as part of its process capability analysis routine (see Figure 7.4b).

Process Capability for Variables Data—One-Sided Specification Limit

The previous discussions dealt with the situation where specifications are two-sided—that is target value ± some value representing the USL and LSL, which is sometimes expressed as from LSL to USL. There are many situations where the specification is one-sided—that is target + 0/–0.002 or not to exceed USL where 0 is ideal. In these cases, the target value is not midway between the LSL and USL. The target value is the LSL. In this case, process capability is measured using C_{pu} or in more precise terms, we measure process capability using C_{pk} where $C_{pk} = C_{pu}$. The assumption of normality in the process data must still be satisfied.

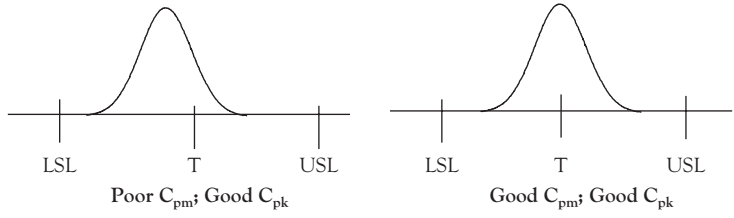


Figure 7.7 Improving C_{pm} through process centering

Example 7.3

Process Capability for One-Sided Specifications

The Environmental Protection Agency maximum concentration level for arsenic in potable water is 0.010 ppm.[11] The ideal or goal is 0 ppm arsenic in the water. This is a situation where the target value is the LSL (0 ppm).

A bottling company extracts water from a well which is then filtered, sanitized using UV radiation, and bottled for sale. Samples from the bottling line are taken periodically and tested for a variety of potential contaminants. Among the tests is one to determine the amount of arsenic present in the water. The process is in control and the distribution of the individual observations is approximately normal. The appropriate measure of process capability for this process would be $C_{pk} = C_{pu}$. Because this is a critical statistic, the company uses a standard of $C_{pk} \geq 2.00$ as their measure of process capability. The measured value of C_{pk} is 2.05, which is above the standard, therefore the process is considered to be capable.

Process Capability for Nonnormal Distributions

The use of C_p, C_{pk}, and C_{pm} require that the process distribution is approximately normal. There are many situations where this might not be the case. It is possible to accommodate nonnormal distributions by identifying the appropriate distribution and selecting it for use when determining process capability. Figure 7.8 shows the process capability parameter selection screen for NWA Quality Analyst.

Example 7.4

Process Capability with Nonnormal Distribution

A manufacturing company tracks the time it takes to prepare shipments from its factory. They use day as the rational subgroup and x-bar and s-charts with variable sample sizes to determine the state of control of the process. The control charts indicate the process is in control. The

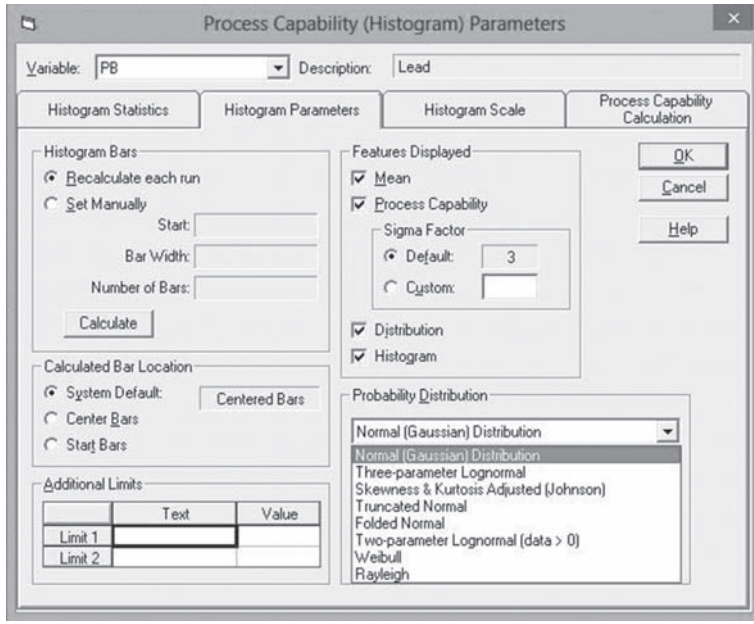


Figure 7.8 Probability distributions available for process capability analysis in NWA Quality Analyst

company has set a goal of 5 minutes per shipment and an upper bound of 10 minutes per shipment and wants to understand the process's capability to meet these specifications.

Their first attempt to assess process capability used the software's default setting of the normal distribution to model their process. The output they obtained is in Figure 7.9.

By visual examination, we can see that the data do not fit the normal distribution, which renders C_{pk} meaningless. The shape of the distribution suggests instead a Weibull[12] distribution.[13] Note that there are statistical tests to determine how well data fit a specific distribution, but for the purpose of this book, we will rely on visual examination. They make the appropriate selection in NWA quality analyst (see Figure 7.8) and obtain Figure 7.10.

Visually, the Weibull distribution is a much better fit for the data. The printout shows that $C_{pk} = 0.9988$ while the company was targeting a $C_{pk} = 1.33$ as their minimum standard. They conclude the process is

not capable as currently designed and initiate an improvement project to increase the capability of the process.

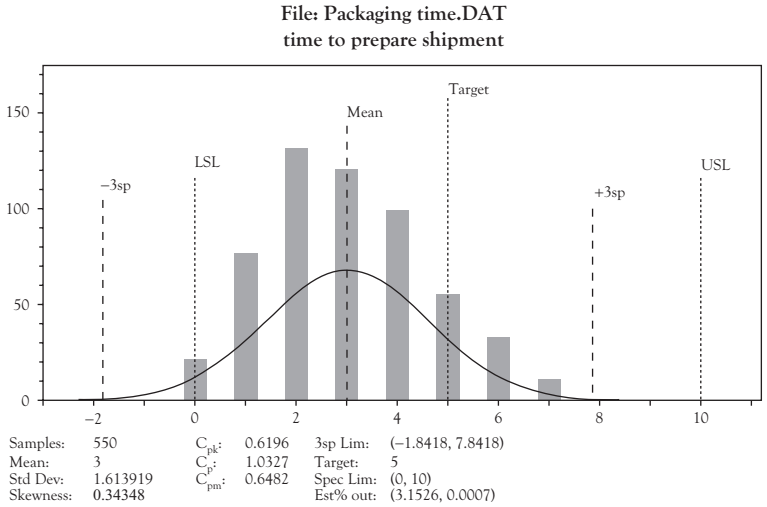


Figure 7.9 Package preparation times modeled using the normal distribution

Source: Created using NWA Quality Analyst 6.3.

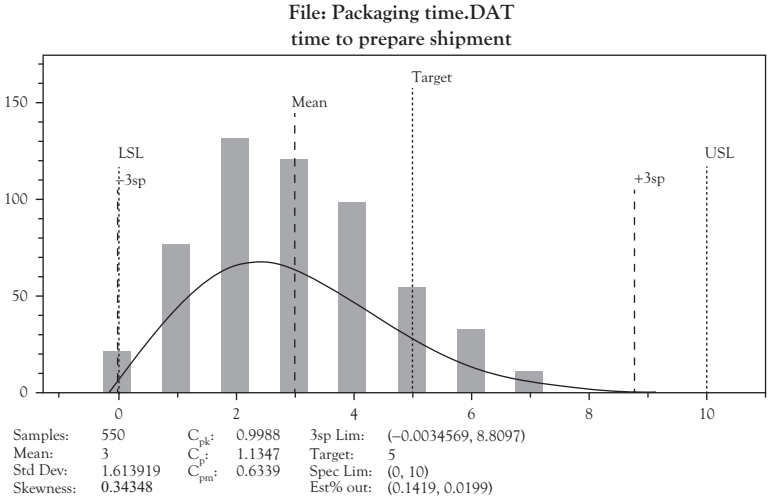


Figure 7.10 Package preparation times modeled using the Weibull distribution

Source: Created using NWA Quality Analyst 6.3.

Process Capability for Attributes Data

Process capability for attributes data is less complex than for variables data. One measure of process capability is the centerline value of the attribute control charts. This works well for p-charts and u-charts, but less well for np-charts and c-charts. To say that a process is capable of producing on average a $\bar{p} = 0.002$ has meaning as a standalone measure and can be used as a predictor. We would expect the process, if it remains in control, to continue to produce a proportion defective of 0.002. Similarly, a $\bar{u} = 0.10$ also has meaning as a standalone measure. We would expect the process, if it remains in control, to continue to produce 0.10 defects per unit.

Neither $\overline{np}$ (the central line for the np-chart) nor $\bar{c}$ (the central line for the c chart) work as well as standalone measures of process capability. The sample size must be included in order for these measures of process capability to be meaningful. The number of defective units in a sample and the number of defects in a sample must have the sample size specified in order to be meaningful. This is cumbersome.

Another popular approach to measuring process capability with attribute data is to use the measure "parts per million defective" sometimes known as the number of defectives per million opportunities. The abbreviations parts per mission (ppm), defects per million opportunities (DPMO), and parts per million defective (ppmd) are variously used with this measure. This is a popular measure in the Six Sigma approach to quality.

Another popular approach involves the use of sigma notation. As Table 7.1 showed, there is a relationship between ppm and the number of standard deviations defining the spread of the specification limits relative to the spread of the process distribution. Three sigma quality coincides to 2,700 ppmd for example. However, care must be taken when using this approach. The Six Sigma quality program allows a $\pm 1.5\sigma$ shift in the process mean when calculating this quality measure. Allowing for this shift, 3σ quality now coincides with 65,000 ppmd instead of 2,700. The Six Sigma program goal of making all processes Six Sigma capable is defined as 3.4 ppmd when the 1.5σ shift is allowed, but 0.002 ppmd when the mean is not allowed to shift.

Regardless of the measure, the organization must determine the process capability necessary to delight its customers. For some 2,700 ppmd is

sufficient; for others, this would represent dreadful performance. Setting the process capability goal is a management responsibility.

Chapter Take-Aways

When a process is centered on the specification target value, there are only two actions that can improve process capability:

- Decrease process variation
- Loosen the specification

When the process is not centered on the specification target value, centering the process can improve process capability.

The process for using process capability indices C_p, C_{pk}, and C_{pm} is:

- Confirm that the specifications accurately reflect the customers' intended purpose.
- Confirm that the process is in control.
- Verify that distribution of individual measurements is approximately normal (or identify and use the appropriate alternative distribution). This should be done using statistical measures of goodness of fit.
- Compare the variation of the in-control process to the spread of the specifications using the appropriate index.
- Determine whether the process capability index meets expectations (e.g., $C_p = 1.33$ or $C_p = 2.00$).

The larger the value of the capability ratio, the larger the magnitude of an unexpected event that can be tolerated without generating large amounts of out-of-specification material.

The goals of process capability are:

- To have all of the variable process indices equal to each other ($C_p = C_{pk} = C_{pm}$), indicating the process is centered on the specification target value, and
- Greater than the organization's standard for considering a process to be capable (e.g., 1.33 or 2.00).

Modern SPC software allows for the easy analysis of process capability for processes that are not normally distributed.

Process capability using attributes data is usually defined in terms of average proportion defective, average number of defects per unit, parts per million defective, or the number of standard deviations defining the spread of the specification limits relative to the spread of the process distribution.

Process capability is useful in predicting the performance of processes and customer satisfaction with the output of those processes. However, the goals for process capability must be set by management to achieve the level of performance demanded by customers.

Questions You Should be Asking About Your Work Environment

- *How well do the specifications for your products and services reflect customer requirements?*
- *How many of your processes have established levels of process capability?*
- *Are all of your processes properly centered on the target value?*
- *Have you established the level of process capability necessary to meet customer requirements?*
- *Is improving process capability an integral part of your continuous quality improvement program?*
- *What gains would accrue to your organization from increasing process capability?*

CHAPTER 8

SPC in Service Industries

When people talk about successful (service providers) and those that are not so successful, the customer determines at the end of the day who is successful and for what reason.

—Jerry Harvey

There are a number of key differences between the design, production, and delivery of a product and the design and delivery of a service. Some of these differences can have an influence on the way statistical process control (SPC) is employed. While the underlying theory is the same, deployment of SPC in the service sector often differs in certain respects from SPC deployment in the manufacturing sector.

Among the key differences between products and services[1] that might affect SPC deployment are:

- Products are generally tangible, while services, even those with a tangible component, tend to be intangible in terms of customer focus.
- In many instances, services are created and delivered at the same time and by the same people. Products tend to be created in advance and different people do the manufacturing and delivery. For this reason, service defects are more often found by customers than in the case of manufacturing.
- Service processes tend to be more visible to customers than manufacturing processes.
- Key quality characteristics (KQC) of services tend to be less quantifiable and can be more subjective than KQCs for products.

In this chapter, we will discuss how these differences manifest in the use of SPC in services.

Defining Quality in Services

Because services tend to be intangible, there often is a human interaction involved between the service provider and the customer, and there is a greater tendency toward and attitude of "beauty being in the eye of the beholder" in services than in manufacturing. For these reasons, defining quality is often more difficult in the service sector. If quality is ill defined, how then are we to judge whether the service is conforming or nonconforming?

A number of attempts have been made to define the dimensions of service quality. Two of these are presented in Table 8.1. The definition developed by Parasuraman et al.[2] seems to be particularly good at highlighting the increased difficulty of defining quality in services. Their definition is that quality of a service is the difference between the customers' expectation and their perception of the quality of the service rendered. Certainly there are aspects of this in product quality as well; however, with products there are usually more objective KQCs such as dimensional conformance that make defining quality somewhat more straightforward.

Table 8.1 Dimensions of service quality

SERVQUAL dimensions*	Dimensions of service quality for hospitals**
Tangibles	Respect & caring
Reliability	Effectiveness & continuity
Responsiveness	Appropriateness
Assurance	Information
Empathy	Efficiency
	Meals
	First impression
	Staff diversity
	Efficacy

Sources: *Parasuraman, Zeithaml, and Berry et al. (1988).

** Sower et al. (2001).

None appear to be universally applicable to all services. For this reason, these attempts should be viewed as starting points for the determination for the true dimensions of quality for the particular services and customers involved.

Rare Events

Some KQCs in service applications are rare events. Examples include surgical errors, lost time accidents, and erroneous tax returns prepared by a certified public accountant CPA. Because these events are so rare, control charts that track defectives (p-charts) and defects (u-charts) are not well suited for these applications. If the rational subgroup (see Chapter 4) is small (for example one work day), there will be many days where the control chart entry is zero. If the rational subgroup is large (for example one month), it will take more than 2.5 years to collect sufficient data to create control charts that fully characterize the process.

One solution is to not use control charts for rare events at all and to treat each rare event as a special cause. Because these events are, by definition, rare, there is little risk of wasting time looking for an assignable cause when only common cause variation is present. The investigation of rare events, however, should take a systems perspective rather than simply attempting to identify and punish the "guilty party." According to Dr. Donna Cananiano, then surgeon-in-chief at Nationwide Children's Hospital, "I would like to know right away if we have an (rare) event today…When you actually look at why the (healthcare professional) makes an error in the first place, it's a systems problem."[3] So, in this approach, the same diligence and methodology should be brought to bear on the investigation of a rare event as with an out of control signal on a control chart.

An alternative solution is to track not the incidence of rare events but the elapsed time between rare events and plot that data on individual and moving range charts. The elapsed time between events can be transformed to a Weibull distribution which is sufficiently approximated by a normal distribution to allow the transformed data to be plotted on individual and moving range control charts or exponentially weighted moving average charts.[4] While this is a better approach for control charting than plotting

the rare event frequency, if the event is truly rare and serious, usually it is better to treat all rare events as if they were due to an assignable cause.

What Chart to Use?

Because services tend to be intangible, it is much more difficult to measure the KQCs for services than for products. While important to product quality, customer expectations and opinions tend to be more important determinants of service quality. Hospitals, for example, are very concerned with patients' opinions about the overall hospital experience during their stays. Hospitals often go to great lengths using focus groups and other tools to determine how patients form their opinions about quality and what factors enter into these decisions. This is very important, because simply measuring factors that are easy to measure without regard for how those factors play into the customer's opinion about quality provides a result that may not be meaningful or useful for driving quality improvement projects. Without this linkage to the customer, even very precise measurements of irrelevant factors will be of little value.

Once the important factors are determined, they are often measured using some form of survey instrument which must be assessed for validity and reliability. A valid and reliable instrument can produce meaningful data—but how do we employ SPC in the evaluation of that data? Often patients respond to survey questions by marking a scale of 1 to 5 or 1 to 7 with one end anchored with something like "Completely Agree" and the other end anchored with something like "Completely Disagree." The responses are discrete data (only integer values are allowed), and are bounded (responses beyond the values in the scale are impossible).

One approach taken by some hospitals is to define a month as a rational subgroup. All of the responses for a particular month are analyzed as one sample. This turns the data set into continuous data bounded by the limits of the scale. The sample means are plotted on an x-bar chart (with variable sample size) and the sample standard deviations are plotted on an s-chart.

Another approach is to define a cutoff scale score that indicates a respondent is dissatisfied. One approach might be to assign the scale midpoint as the cutoff between a satisfied and a dissatisfied respondent as

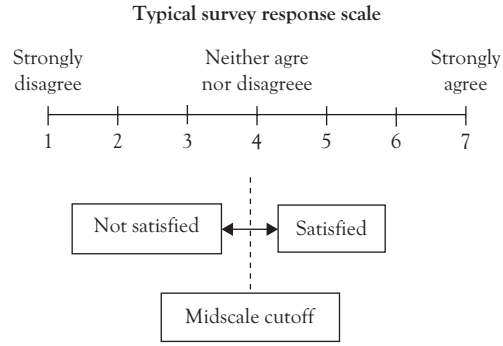


Figure 8.1 Typical survey response scale

shown in Figure 8.1. Other organizations that aspire to delight customers might set the cutoff scale score higher. Each respondent can be classified as a satisfied or dissatisfied customer and that data can be used to construct a p-chart. Example 8.1 illustrates the use of a p-chart using survey data in this way.

Examples of SPC Usage in Service Organizations

Example 8.1

Control Charts in Healthcare

A hospital launched a project to increase patient satisfaction with meals. The effort was spurred by two things:

- Research by Dr. Susan Schiffman at Duke University Hospital about the clinical importance of making meals more palatable so that patients want to eat, and
- The success of initiatives at hospitals such as M.D. Anderson Cancer Center and Medical Center Dallas to place the patient in the center of what a hospital does by offering more choice in meals.

Because the major commission that accredits healthcare organizations encourages the use of appropriate statistical tools in performance

measurement, the hospital decided to incorporate SPC into the project. Based on focus groups conducted with recently discharged patients, the hospital developed a four-question survey they used to obtain feedback from patients as they were discharged about food service quality. The patients responded to the four statements using a 7-point scale, with 7 representing "strongly agree" and 1 representing "strongly disagree." Any patient who responded to any one of the three items with a scale score below 4 was considered to be dissatisfied with the meal experience. The initial analysis revealed that more than 10 percent of patients were dissatisfied, and the most frequently cited reason for dissatisfaction was food taste.

Analysis of the focus group information revealed that patients judged the taste of the food by comparing it with their expectations. This led to two obvious ideas for decreasing the level of dissatisfaction:

- Patients on a liquid or bland diet who have steak and potatoes expectations were certain to be dissatisfied with hospital meals. The hospital decided to have a representative of the dietetics department meet with each patient to explain the diet specified by their physician and the necessity for that diet. This helped align the patients' expectations with the restrictions of their prescribed diets.
- The patients were offered choices within the scope of their diets. No longer would a patient automatically receive green gelatin and chicken broth. They could choose from several flavors of gelatin and alternatives to chicken broth. This gave them some control over their dietary decisions.

As the control chart in Figure 8.2 shows, this project was very effective. The proportion of patients dissatisfied with hospital meals was reduced from more than 10 to 7 percent—a 30 percent improvement.

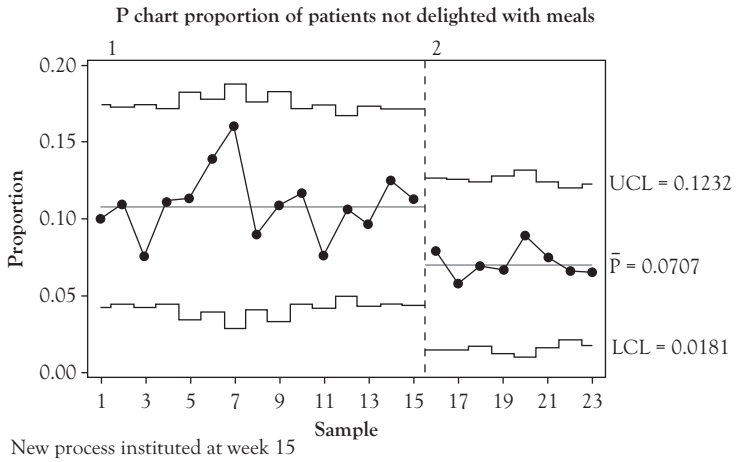


Figure 8.2 p-chart for survey data

Source: Created using Minitab 16.

Example 8.2

Control Charts in Retail

A locally owned hardware store was concerned about competition from the national chain building supply store that had recently located in their market area. Since the chain store had significantly greater buying power, price was not a feasible way to compete. Inspired by a news story about a building supply store that offered extraordinary guarantees, they decided that was one way they could beat the competition. They settled on the following extraordinary guarantee: "We guarantee that we will have what you want from our normal offerings in stock or we will provide it to you free within 24 hours!"

Since the cost of expedited shipping and free merchandise associated with a stockout under this guarantee can be very high, they felt they needed to assess how well their system was prepared to support it. They collected data each day on the number of customers served and the number of stockouts. They constructed a p-chart to analyze the data and to assess how well their process was prepared for to support the extraordinary guarantee.

The p-chart shows that their process is in control; however, the average percent ($\bar{p}$ = 0.04606) of customers who asked to purchase an item that was out of stock was too high to be economically feasible to support the extraordinary guarantee. The owners determined that the process must be capable of achieving ($\bar{p} \leq 0.01000$) in order for the extraordinary guarantee to be feasible. Projects to improve their forecasting and inventory management policies were instituted with a goal process capability of ($\bar{p} \leq 0.01000$) within 6 months.

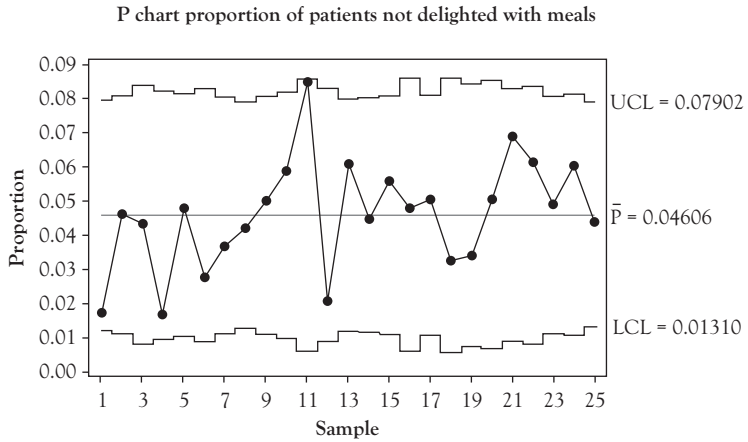


Figure 8.3 p-chart for stockout data

Example 8.3

Control Charts in Finance

The accounts payable department of a large corporation processes more than 1,000 invoices per day. On a randomly selected day each week, 100 invoices are selected at random and reviewed for errors by the assistant manager of the department. In the past, the information was used to identify which accounting clerks were making errors. The offending clerks were warned to pay closer attention to their jobs to avoid further errors. Whenever the number of errors was above 4, all of the clerks were warned that they must do better.

A newly appointed assistant manager decided to use quality tools to assess the entire process. She constructed a p-chart to analyze the weekly sample of invoices. To her surprise, she found that the process was in control, however the overall proportion of invoices with errors in the samples was higher than she felt was necessary.

Further investigation revealed that the training process for newly hired clerks and the continuing education process for existing clerks were not as robust as she thought they should be. In addition, a number of invoices submitted for processing lacked critical information.

The assistant manager redesigned the training programs for the clerks and held seminars for the departments that submitted invoices for payment stressing the necessity for provision of complete and accurate information. She also halted the practice of department-wide meetings when errors exceeded an arbitrary limit. After a few months, the assistant manager observed a signal of 8 points in a row below the CL on the p-chart. This indicated that the changes she had made were effective, and she revised the control limits to reflect the state of the new process.

Chapter Take-Aways

- While there are key differences between the manufacture of products and the delivery of services, SPC is equally applicable in both sectors.
- Care must be taken when attempting to apply SPC to monitor rare events. Traditional control charts may not be the best option.
- Selection of the right control chart for a particular service application might not be as straight forward as in manufacturing applications.
- Specific examples were provided for the use of SPC in healthcare, retail, and financial services applications.

Questions You Should be Asking About Your Work Environment

- *How do you define quality for the services you provide? Were customers included in the discussion before the quality definition was established?*
- *How do you know whether you are satisfying or delighting your customers?*
- *Have you resisted using SPC because it is a "manufacturing tool" not applicable to services? How might you improve your operation if you implemented SPC?*
- *Do you have a continuous improvement (CI) program in place? How do you know how effective it is? Could you provide proof to an outsider who asked about your CI program's effectiveness?*

APPENDIX A

Bare Bones Introduction to Basic Statistical Concepts

I said at the beginning of this book that we would not get overly involved with statistics and manual calculations. There are many books available to those who wish to delve more deeply into the details of the statistics and manual calculations of SPC. These include Montgomery,[1] Duncan,[2] and Sower.[3] For our purposes, we will utilize statistical analysis software for the calculations. However, it is important to understand some basic statistical concepts in order to make informed decisions about which tools available in the software to use for specific situations and understand the output received from the use of those tools. This section will focus on basic statistical concepts from a conceptual perspective rather than from a detailed theoretical and manual calculation perspective.

Distributions

When we collect data from a process periodically over time, the data are arranged in a time series with the earliest data listed first as shown in Table A.1. This is the data format used for creating run charts and control charts.

However, it is sometimes useful to reorganize the data based on the frequency with which specific values occur in order to better understand how the data are distributed. This is the data format used for process capability analysis and to visually assess the nature of the distribution. A good tool for showing the data in this latter format is the histogram as shown in Figure A.1.

What can we learn from organizing the data in this way and depicting it using a histogram? For one thing, we can see that the average or mean of this distribution of values appears to be somewhere near 10. The most frequently observed value (the value with the highest bar), called the mode,

Table A.1 Data C1 arranged in time series

Time period	Observation C1	Time period	Observation C1	Time period	Observation C1
1	7	16	12	31	9
2	8	17	11	32	10
3	12	18	9	33	13
4	10	19	11	34	10
5	14	20	6	35	8
6	11	21	10	36	7
7	9	22	8	37	10
8	9	23	12	38	12
9	7	24	9	39	9
10	11	25	4	40	11
11	8	26	10	41	6
12	13	27	9	42	10
13	10	28	11	43	8
14	11	29	10	44	9
15	10	30	15	45	11

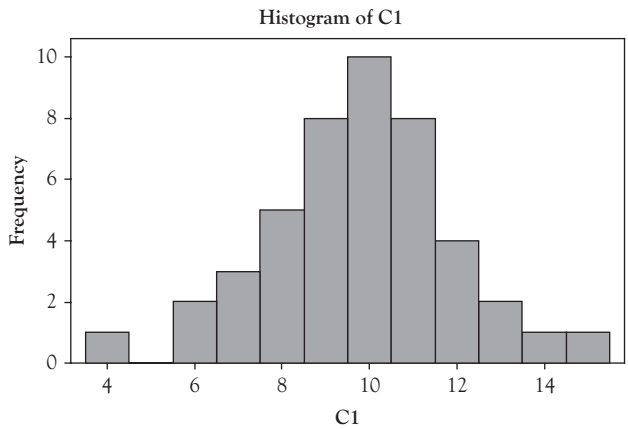


Figure A.1 Frequency histogram for data C1

Source: Created using Minitab 16.

is 10. The maximum value is 15 and the minimum value is 4. Subtracting the minimum from the maximum value (15 – 4 = 11) gives one measure of the spread of the distribution called the range. The range is 11. The larger the range, the greater the spread of the distribution. We also can

see that shape of the distribution appears to be approximately normal or bell-shaped. ASQ defines a normal distribution as one where "most of the data points are concentrated around the average (mean), thus forming a bell shaped curve."[4] In fact, we can have Minitab fit a normal curve to the data set as shown in Figure A.2.

As you see, when we fit a normal curve to the histogram, Minitab reports other information as well. The mean of the data is 9.778, which is close to the estimate we determined by examination of around 10. Instead of the range, Minitab reports standard deviation (StDev) which, like the range, is a measure of the spread of the data. As with the range, the larger the value of the standard deviation, the greater the spread of the data. The standard deviation of the data is 2.152. Minitab also reports that there are 45 individual data points in this data set. We can also see that the fit of the normal curve to the data is not perfect. The fit can be assessed quantitatively using Minitab, which, however, is beyond the scope of this section. Suffice it to say that by eye, the fit appears to be pretty good but not perfect.

It is important to recognize that the normal curve is not a good fit for all data distributions. To assume that all data are normally distributed is a fundamental error in statistics. Indeed, there are many data sets that cannot be accurately modeled using any standard distribution. However,

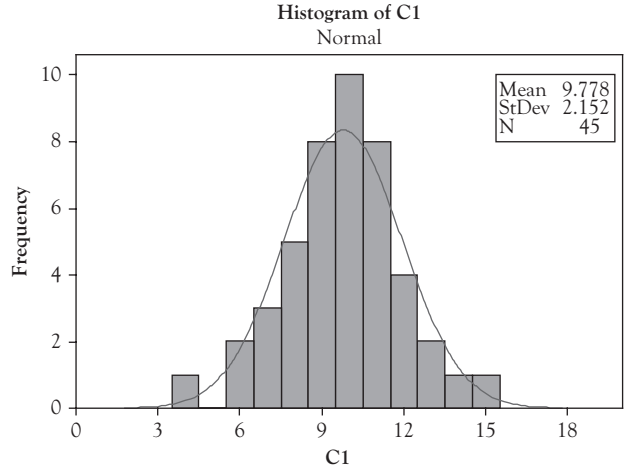


Figure A.2 Frequency histogram for data set C1 with normal curve fitted

Source: Created using Minitab™.

the concepts we discuss here using the normal curve are applicable to all standard distributions.

The normal distribution is a probability distribution, which means we can use the information it provides to determine the proportion of the total data set which can be expected to be found in different regions of the curve as defined by the standard deviation. This is a very useful feature for SPC. Figure A.3 shows a normal probability distribution for a population with the area under the curve divided into regions based on the number of standard deviations above and below the mean. In this figure, we use the Greek letter mu (μ) to represent the population mean or average and the Greek letter sigma (σ) to represent the population standard deviation. (I know I promised to limit my use of Greek letters, but trust me, these are important.) The mean and the standard deviation of a sample taken from a population are represented by $\bar{x}$ and s, respectively.

Statistical theory tells us that we can use the area under the normal probability distribution to estimate the percentage of observations that will fall within a certain number of standard deviations on either side of the mean. This is called the empirical rule. This is illustrated using the values for the mean and standard deviation taken from Figure A.2. For example, we can say that about 99.73 percent of all of the values in the normal distribution fall in the area between $\mu - 3\sigma$ and $\mu + 3\sigma$. Theoretically, the normal distribution stretches from negative infinity ($-\infty$) to positive infinity ($+\infty$). Therefore about 0.27 percent (1 – 99.73%) of the

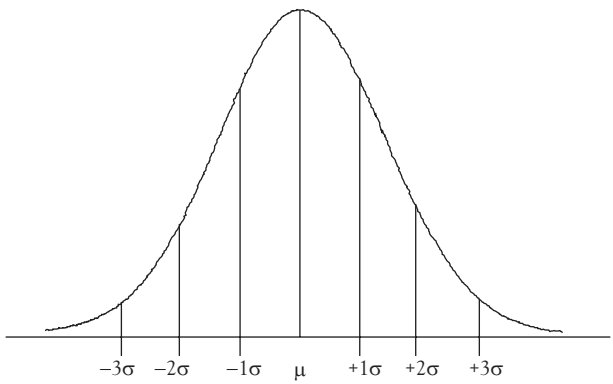


Figure A.3 The normal distribution with standard deviations shown

Table A.2 The empirical rule applied to the distribution in Figure A.2

Standard deviations	Range of values	% of population
$\mu \pm 1\sigma$	7.626 – 11.930	~ 68.26%
$\mu \pm 2\sigma$	5.474 – 14.082	~ 95.46%
$\mu \pm 3\sigma$	3.322 – 16.234	~ 99.73%

values in the distribution will fall outside the $\mu \pm 3\sigma$ range—that is, in the tails of the distribution from $+3\sigma$ to $+\infty$ and from -3σ to $-\infty$. Since the normal probability distribution is symmetrical, half of that 0.27 percent falls in each tail. Additional statistical theory also tells us that this general concept applies in the same conceptual way to other standard probability distributions.[5]

Example A.1
Using the Empirical Rule

Using the normal distribution in Figure A.2 and the empirical rule in Table A.2, we see that 68.26 percent of the values can be expected to fall between $\pm 1\sigma$ of the mean. One standard deviation below the mean is 9.778 – 2.152 = 7.626. One standard deviation above the mean is 9.778 + 2.152 = 11.930. Therefore, we can say that 68.26 percent of the values in this distribution can be expected to fall between 7.626 and 11.930.

Samples and Individuals

SPC uses statistics derived from both samples and individuals. It is important to understand when to use each. This is especially true when dealing with x-bar charts and process capability analysis as discussed in Chapter 7. Figure A.4 illustrates the relationship between the distribution of sample means and the distribution of the individual observations that comprise the samples. While the means will be the same, the spread, measured by the range or standard deviation, of the distribution of individuals will always be greater than the standard deviation of the distribution of sample means.

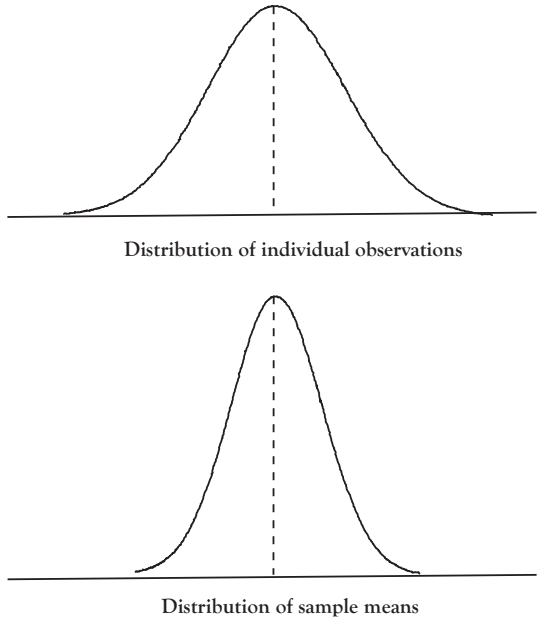


Figure A.4 Sample statistics versus process statistics

The process standard deviation (σ_x) is calculated for comparison to the tolerance or specification limits when calculating process capability. The process standard deviation (σ_x)(the standard deviation of the individual observations) will always be larger than the standard deviation of the sample means ($\sigma_{\bar{x}}$). The standard deviation of the sample means ($\sigma_{\bar{x}}$) is used when calculating control limits for the x-bar chart. It is very important to use the appropriate standard deviation for the intended purpose.

Figure A.5 illustrates this point by providing a numerical example to illustrate the relationship between the distribution of sample means and the distribution of the individual observations.

There is a mathematical relationship between the standard deviation of the sample means and the standard deviation of the individual observations. To obtain an estimate of the standard deviation of the sample means ($\sigma_{\bar{x}}$), divide the standard deviation of the individual observations (σ_x) by the square root of the sample size ($\sqrt{n}$) as shown below.

$$\sigma_{\bar{x}} = \frac{\sigma_x}{\sqrt{n}}$$

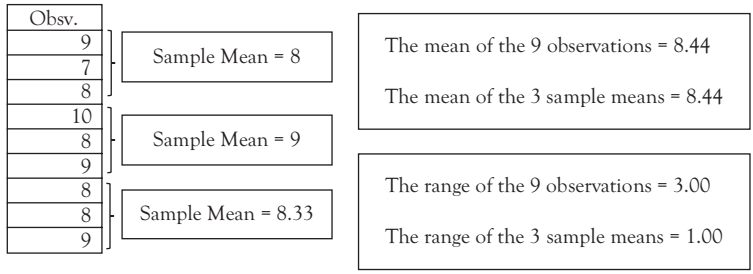


Figure A.5 Mean and standard deviation comparison—individuals versus sample means

Since the square root of the sample size for all sample sizes is greater than 1, mathematically, the standard deviation of the distribution of the sample means will always be smaller than the standard deviation of the distribution of the individual observations.

Control Chart Calculations

Chapters 4 through 6 discuss the selection and use of a variety of control charts for both variable and attribute data. The formulas for calculating the control limits for the control charts discussed in these chapters are in Table A.3 where:

UCL = upper control limit
LCL = lower control limit
CL = central line
σ_x = standard deviation of the individual observations
$\sigma_{\bar{x}}$ = standard deviation of the sample means
n = the number of observations in each sample or subgroup
k = the number of samples or subgroups
$\bar{x}$ = the sample mean
$\bar{\bar{x}}$ = the mean of the sample means; the grand mean
Δ = Delta statistic (measured value – nominal value)
$EWMA = \alpha y_t + (1 - \alpha)\, EWMA_{t-1}$
α = *EWMA* weighting factor
y_t = the individual observation at time t
$\bar{y}$ = the mean of the individual y_i

$EWMA_{t-1}$ = the previous period's EWMA
p = proportion of defective or nonconforming units in a sample
$\bar{p}$ = the mean of the sample proportion defective or nonconforming units; the grand average proportion defective or nonconforming
np = the number of defective or nonconforming units in a sample
$\overline{np}$ = the mean number of defective or nonconforming units per sample; the grand average number defective or nonconforming
c = the number of defects or nonconformities in a sample
$\bar{c}$ = the mean number of defects or nonconformities per sample; the grand average number of defects or nonconformities per sample
u = the number of defects or nonconformities per unit in a sample
$\bar{u}$ = the mean number of defects or nonconformities per unit; the grand average number of defects or nonconformities per unit

Process Capability Calculations

Chapter 7 discusses the selection and use of different index measures of process capability. The formulas for calculating these indexes are in Table A.4 where:

USL = upper specification limit
LSL = lower specification limit
T = specification target value
μ = process mean
σ_x = standard deviation of the individual observations
n = number of observations

Table A.3 Control limit calculations

Control chart	CL	UCL	LCL
Individual	$CL = \bar{x} = \frac{\sum_{i=1}^{k} x_i}{k}$	$UCL = \bar{x} + 3\sigma_x$	$LCL = \bar{x} - 3\sigma_x$
Moving range	$CL = \overline{MR} = \frac{\sum_{i=1}^{k} (x_i - x_{i-1})}{k}$	$UCL = \overline{MR} + 3\sigma_{MR}$	$*LCL = \overline{MR} - 3\sigma_{MR}$
X-Bar	$CL = \bar{\bar{x}} = \frac{\sum_{i=1}^{k} \bar{x}_i}{k}$	$UCL = \bar{\bar{x}} + 3\sigma_{\bar{x}}$	$LCL = \bar{\bar{x}} - 3\sigma_{\bar{x}}$
Range	$CL = \bar{R} = \frac{\sum_{i=1}^{k} R_i}{k}$	$UCL = \bar{R} + 3\sigma_R$	$*LCL = \bar{R} - 3\sigma_R$
Standard deviation	$CL = \bar{s} = \frac{\sum_{i=1}^{k} s_i}{k}$	$UCL = \bar{s} + 3\sigma_s$	$LCL = \bar{s} - 3\sigma_s$
Delta	$CL = \bar{\bar{\Delta}} = \frac{\sum_{i=1}^{k} \Delta_i}{k}$	$UCL = \bar{\bar{\Delta}} + 3\sigma_{\bar{\Delta}}$	$*LCL = \bar{\bar{\Delta}} - 3\sigma_{\bar{\Delta}}$
EWMA	$CL = \bar{y} = \frac{\sum_{i=1}^{k} y_t}{k}$	$UCL = \bar{y} + 3\sigma_y$	$LCL = \bar{y} - 3\sigma_y$
p	$CL = \bar{p} = \frac{\sum_{i=1}^{k} p_i}{k}$	$UCL = \bar{p} + 3\sigma_p$	$*LCL = \bar{p} - 3\sigma_p$
np	$CL = n\bar{p} = \frac{\sum_{i=1}^{k} np_i}{k}$	$UCL = n\bar{p} + 3\sigma_{np}$	$*LCL = n\bar{p} - 3\sigma_{np}$
c	$CL = \bar{c} = \frac{Total\ Defects}{k}$	$UCL = \bar{c} + 3\sigma_c$	$*LCL = \bar{c} - 3\sigma_c$
u	$CL = \bar{u} = \frac{\sum_{i=1}^{k} u_i}{k}$	$UCL = \bar{u} + 3\sigma_u$	$*LCL = \bar{u} - 3\sigma_u$

* *Set* LCL to zero if negative.

Note: In this table, the formulas for UCL and LCL are for control limits set at 3σ above and below the central line. If it is desired to set control limits at other than 3σ, simply replace the 3 with the number of standard deviations (σ) desired.

Table A.4 Process capability indexes

Index	Equation
C_p	$C_p = \frac{USL - LSL}{6\sigma_x}$
C_{pl}	$C_{pl} = \frac{\mu - LSL}{3\sigma_x}$
C_{pu}	$C_{pu} = \frac{USL - \mu}{3\sigma_x}$
C_{pk}	$C_{pk} = minimum(C_{pl}, C_{pu})$
C_{pm}	$C_{pm} = \frac{USL - LSL}{6\sqrt{\sum_{i=1}^{n} \frac{(x_i - T)^2}{n-1}}}$

Appendix Take-Aways

In this appendix, we reviewed some statistical concepts that are keys to SPC. We did not delve deeply into statistical calculations and statistical theory—in fact to say that we have merely scratched the surface is a significant understatement. See the references listed at the beginning of this section for more detail.

Statistical Terms[6]

- Binomial distribution—A frequency distribution that "describes the behavior of a count variable x if the following conditions apply: (1) The number of observations n is fixed; (2) Each observation is independent; (3) Each observation represents one of two outcomes ('success' or 'failure'); (4) The probability of 'success' (p) is the same for each outcome."[7]
- Histogram—"A graphic summary of variation in a set of data. The pictorial nature of a histogram lets people see patterns that are difficult to detect in a simple table of numbers."

- Mean—"A measure of central tendency; the arithmetic average of all measurements in a data set."
  - Population mean—symbol μ (also applied to process mean)
  - Sample mean—symbol $\bar{x}$
  - Grand mean (mean of all the sample means)—symbol $\bar{\bar{x}}$
- Normal distribution—"The charting of a data set in which most of the data points are concentrated around the average (mean), thus forming a bell-shaped curve."
- Poisson distribution—"A discrete probability distribution that expresses the probability of a number of events occurring in a fixed time period if these events occur with a known average rate, and are independent of the time since the last event."
- Range—"The measure of dispersion in a data set (the difference between the highest and lowest values)." Symbol R.
- Standard deviation—"A computed measure of variability indicating the spread of the data set around the mean."
  - Population standard deviation—symbol σ
  - Sample standard deviation—symbol s
  - Standard deviation of the sample means—symbol $\sigma_{\bar{x}}$
  - Standard deviation of the individuals—symbol σ_x

APPENDIX B

SPC Software Used to Illustrate this Book

Minitab 16

- Full-featured statistical analysis package with full SPC capability.
- Easy to use, menu driven, spreadsheet-like data input.
- Home Page: http://www.minitab.com/en-US/default.aspx
- 30-day free trial at: http://www.minitab.com/en-US/products/minitab/

NWA Quality Analyst 6.3

- SPC package with some additional statistical analysis capability.
- Easy to use, menu driven, spreadsheet-like data input.
- Home Page: http://www.nwasoft.com/products/nwa-quality-analyst
- 30 day free trial at: http://marketing.nwasoft.com/acton/fs/blocks/showLandingPage/a/1578/p/p-0055/t/page/fm/0

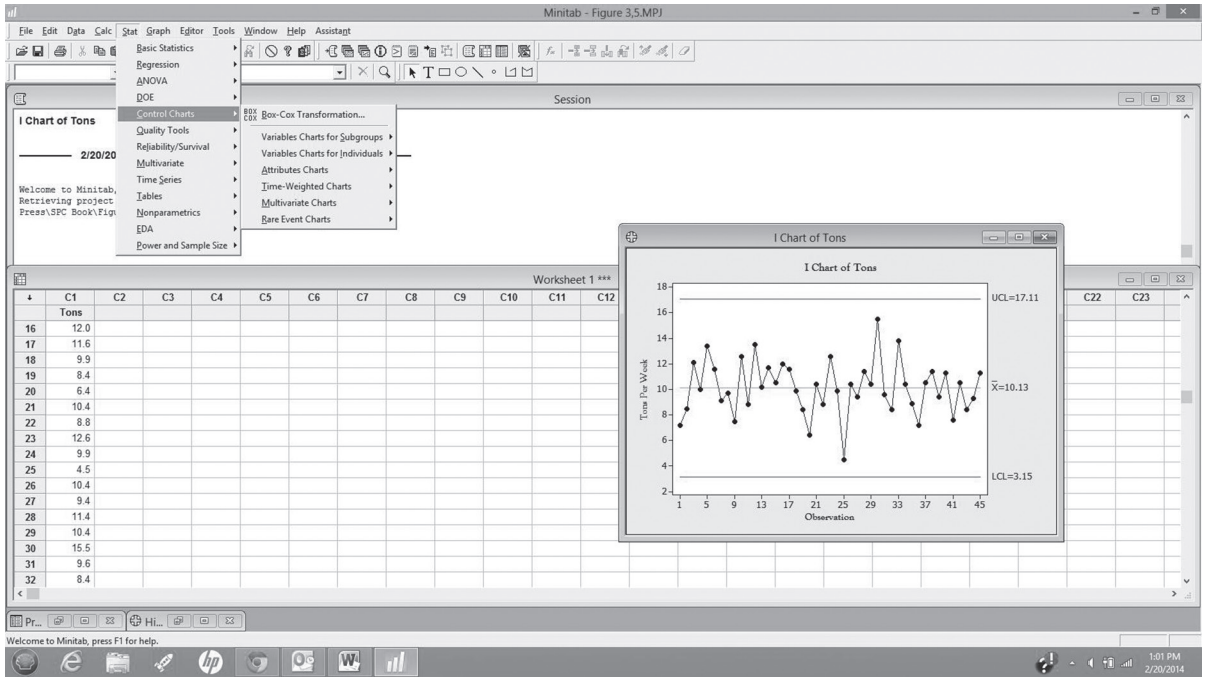


Figure B.1 Screen shot of Minitab 16. Showing data entry, pull down menu, and control chart

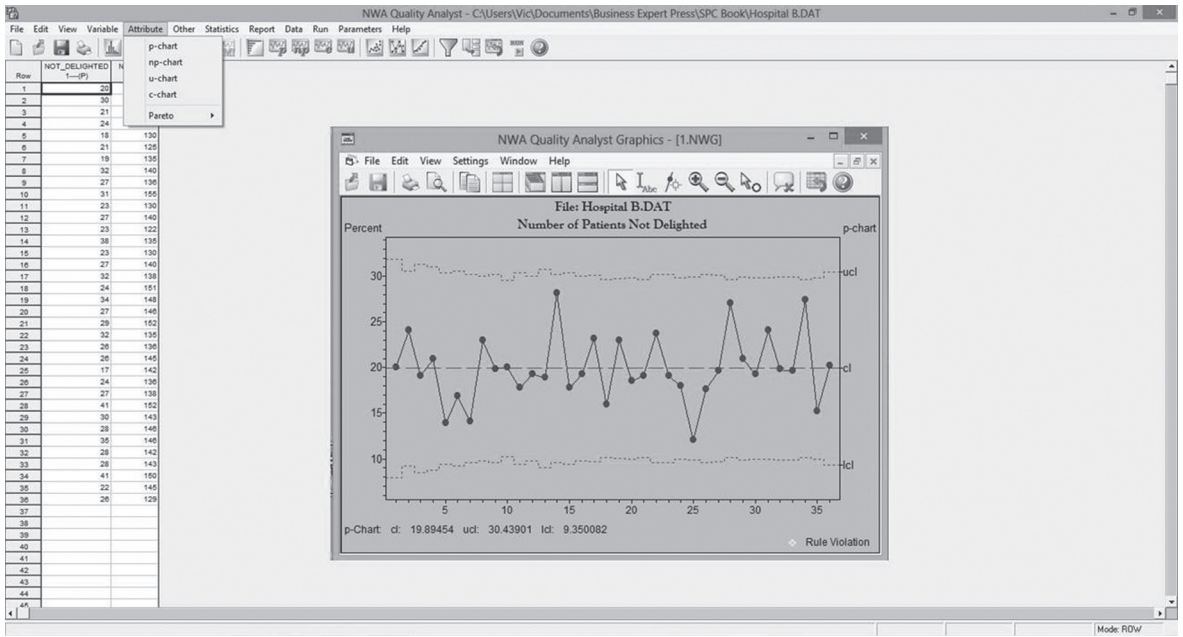


Figure B.2 Screen shot of NWA quality analyst 6.3. Showing data entry, pull down menu, and control chart

Notes

Abstract

1. Balestracci (2014).

Chapter 1

1. ASQ (n.d.).
2. Stevenson (2009), p. 188.
3. A pro forma P&L is a forecast for the expected profit and loss that an organization expects to make in a specified period.
4. ASQ (n.d.).
5. Sower and Bimmerle (1991, March).
6. Walton (1986), p. 75.
7. Taguchi, Chowdhury, and Wu (2005), pp. 133–138.
8. The terms mean and standard deviation are discussed in Appendix A.
9. Sower (1990).
10. Sower (1993), pp. 41–45.

Chapter 2

1. Shewhart (1931).
2. ASQ Online Quality Glossary (n.d.).
3. ASQ Online Quality Glossary (n.d.).
4. ASQ Online Quality Glossary (n.d.).
5. ASQ Online Quality Glossary (n.d.).
6. Deming (1986), pp. 327–332.
7. ASQ Online Quality Glossary (n.d.).
8. For a more complete discussion of metrology see Chapter 9 in Sower (2011); ASQ Measurement Quality Division (2004).
9. ASQ Online Quality Glossary (n.d.).
10. ASQ Online Quality Glossary (n.d.).
11. Sower (2011).
12. For a more complete discussion of gauge R&R study see Chapter 9 in Sower (2011); ASQC Automotive Division (1986).
13. Sower (2011).
14. Sower, Duffy, Kilbourne, Kohers, and Jones (2001).

Chapter 3

1. ASQ Online Quality Glossary (n.d.).
2. Standard deviation is a measure of the variation (spread) of the data around the mean. See Appendix A.
3. ASQC Statistics Division (1983), p. 30.
4. While it is most common to use 3 standard deviations for control charting, sometimes it is appropriate to use other values, for example 2 or 4 standard deviations, instead of 3. This choice depends upon a number of things the most important of which is the relative cost for missing an out of control signal versus obtaining a false signal. Further discussion of this point is beyond the scope of this book. The reader is directed to the references—particularly to Montgomery (2009), Duncan (1986), and Sower (2011).
5. Sower (2011), p. 232; Montgomery (2009), p. 198.
6. The next three chapters will provide guidance for determining what type of control chart to use for different types of data.
7. Borror, Montgomery, and Runger (1999).
8. Western Electric (1956).

Chapter 4

1. Institute for Supply Management (n.d.).
2. ASQ Online Quality Glossary (n.d.).
3. Duncan (1986); Sower (2011).
4. Evans and Lindsay (2005).

Chapter 5

1. Sower, Motwani, and Savoie (1994).
2. National Institute for Standards and Technology (n.d.).
3. Okes and Westcott (2001), p. 107.

Chapter 6

1. ASQ Online Quality Glossary (n.d.).
2. ASQ Online Quality Glossary (n.d.).
3. ASQ Online Quality Glossary (n.d.).

Chapter 7

1. Sower and Fair (2012), pp. 4–9.
2. Sower (2011), p. 6.
3. Schmidt (2013), p. 24.
4. Guaspari (1985), p. 68.
5. Kotz and Lovelace (1998).
6. Montgomery (2009).
7. ASQ Online Quality Glossary (n.d.).
8. Taguchi, Chowdhury, and Wu (2005).
9. Roy (1990).
10. DataNet Quality Systems (n.d.).
11. EPA (n.d.).
12. The Weibull distribution is a continuous distribution related to the exponential distribution. It is most widely used to model failure rates, but can sometimes be used to model data such as that in this example.
13. Note: Even though the individual data fit a Weibull distribution, the sample means are distributed approximately normally. This is not unexpected since statistical theory says that the means of large samples drawn from a nonnormal distribution will tend to be distributed normally. For this reason and because the X-bar chart has been shown to be robust to nonnormality, the choice of x-bar and s-charts is appropriate for this process.

Chapter 8

1. Stevenson (2009).
2. Parasuraman, Zeithaml, and Berry (1988).
3. Sower, Duffy, and Kohers (2008), pp. 115, 121.
4. Montgomery (2009).

Appendix A

1. Montgomery (2013).
2. Duncan (1986).
3. Sower (2011).
4. ASQ Online Quality Glossary (n.d.).
5. For more information see Chebyshev's Theorem at http://www.oojih.com/show/stat1/cheby_empirical/
6. Except where noted, all definitions from ASQ Online Quality Glossary (n.d.).
7. Department of Statistics (n.d.).

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ASQC Automotive Division. 1986. *Statistical Process Control Manual.* Milwaukee, WI: ASQC Quality Press.

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Statistical Process Control for Managers

Victor E. Sower

If you have been frustrated by very technical statistical process control (SPC) training materials, then this is the book for you. This book focuses on how SPC works and why managers should consider using it in their operations. It provides you with a conceptual understanding of SPC so that appropriate decisions can be made about the benefits of incorporating SPC into the process management and quality improvement processes.

Today, there is little need to make the necessary calculations by hand, so the author utilizes Minitab and NWA Quality Analyst—two of the most popular statistical analysis software packages on the market. Links are provided to the home pages of these software packages where trial versions may be downloaded for evaluation and trial use.

The book also addresses the question of why SPC should be considered for use, the process of implementing SPC, how to incorporate SPC into problem identification, problem solving, and the management and improvement of processes, products, and services.

Victor (Vic) Sower is distinguished Professor Emeritus of Operations Management at Sam Houston State University (SHSU). He has a BS in chemistry from Virginia Tech, an MBA from Auburn University, and PhD in operations management from the University of North Texas. Before entering the academic arena at SHSU, Vic worked for 18 years in a variety of manufacturing positions including as a process engineer for the Radford Army Ammunition Plant, and process engineer and process development engineering manager for Ampex Corp. At SHSU, he established the Sower Business Technology Laboratory in the College of Business, is the author or coauthor of eight books in the quality and operations management fields, and is a senior member of American Society for Quality and American Institute of Chemical Engineers.

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