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Summary: Quality Methods

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Quality Methods Overview

To study and characterize process variation over time, we use statistical methods to separate the random variation from the uncontrolled or unexpected sources of variation. The random variation is called *common cause variation*. This is variation that is inherent to the process. A process that exhibits only common cause variation is said to be *stable*, or *in control.* A stable process is predictable.

Unusual or unexpected shifts or changes in the process are called *special causes* of variation. These causes are external, or not inherent, to the process. Because these causes are not predictable, future process performance is not predictable. A process that exhibits special causes of variation is said to be *unstable*, or *out of control*.

Introduction to Control Charts

A *control chart* is a time-ordered plot of data used to study process behavior over time. Control charts enable you to visualize, understand, and quantify the variation in the process.

All control charts have four key components:

1. a time axis to show the time ordering,
2. a statistic that is plotted at regular time periods,
3. a center line, representing the overall process average, and
4. upper and lower control limits, representing the range of variation we can expect if the process is stable, or in control

The plotted statistic can be individual measurements, or the statistic can be computed from samples, like sample means or sample proportions. Because of our understanding of the Central Limit Theorem, we place control limits at approximately +/- 3 standard deviations of the plotted statistic. If a point falls outside these limits, it is likely that this point is a special cause.

There are different types of control charts for plotting different types of process measures. The most commonly used control charts are for plotting continuous measures, like thickness, diameter, and width. These are referred to as *variables* control charts, or Shewhart charts.

There are also control charts for plotting attribute data, like the number of defects or the proportion of defective units. These charts are called *attributes* control charts. A wide variety of specialty control charts are also available.

Individual and Moving Range Charts

The simplest and most popular type of variables control chart is the individual and moving range, or I and MR, chart. The individual (or individuals) chart, is a plot of each data point in time order. The center line on the chart is the average of all the values. The moving range chart is for plotting the variability between observations.

The upper and lower control limits on the individuals chart are based on the short-term, within-subgroup estimate of the standard deviation, where subgroups consist of pairs of consecutive points. This makes the chart more sensitive to detecting special causes.

Because subgroups are selected in a *rational* manner, we refer to them as *rational subgroups*.

Common Cause versus Special Cause Variation

If a process is in control and on target, trying to improve the performance of the process by tweaking machines or work methods generally makes things worse. These efforts to improve a stable process, without knowledge of cause and effect, are known as *tampering*.

The funnel experiment was developed by W. Edwards Deming to illustrate to managers the effects of tampering. The funnel experiment demonstrates that well-intended efforts to improve a stable process, without knowledge of cause and effect, can make things much worse.

If you react to common cause variation as though it is special cause variation, you might actually increase variation, drive the process off target, or create other problems. To reduce common cause variation, you need to understand the process and use data and statistical tools to manage the sources of variation. Special cause variation is external to the process. To eliminate special cause variation, you need to identify the special cause, understand what changed, and take action to prevent the change from happening again in the future.

Testing for Special Causes

A control chart can result in two types of errors:

- The chart can fail to signal or detect a special cause. In statistics, this is called a *false negative*.
- Or the chart can erroneously signal a special cause when there is only common cause variation. This is called a *false positive* or a *false alarm*.

If you see a point outside the control limits, you have a pretty good indication that it is a special cause, especially if the point falls far beyond one of the control limits.

There are other types of special causes, and these might not be as easy to detect. To make a Shewhart control chart more sensitive to detecting special causes, you can test a number of rules. The most common rules are the set of eight Western Electric Rules. Tests for these rules are conducted by dividing the intervals between the overall average and the control limits into zones, where each zone is 1 standard deviation wide.

Each test looks for the occurrence of points in the different zones, signaling if something unlikely, or special, has occurred. Most of the tests identify patterns in the data that are unlikely to occur unless something in the process has changed. However, some of the tests are used to identify potential issues with the rational subgrouping or sampling.

X-Bar and R and X-Bar and S Charts

Data from rational subgroups can be plotted on an X-bar and R chart or an X-bar and S chart. The subgroup means are plotted on an X-bar chart. You use this chart to monitor subgroup means over time. The center line of the X-bar chart is the average of the subgroup means, or the *grand mean*. Because you use sample means, you place the upper control limits at +/- 3 standard errors of the mean.

The subgroup ranges or standard deviations are plotted on a second chart, either an R (or range) chart or an S (or standard deviation) chart. This chart monitors the within-subgroup variability over time.

Rational Subgrouping

A rational subgroup is a non-random sample that has the following properties:

- The observations are from a single process,
- the observations are from a stable process,
- the observations are time ordered, and
- the observations are independent from one another – that is, the value of one observation is not influenced by the value of another observation.

With rational subgrouping, parts are selected in a way that minimizes the possibility that the subgroup contains a special cause. The short-term, or within, estimate of the standard deviation from rational subgroups is likely to represent only common cause variation. This results in tighter control limits and a control chart that is better at detecting special causes.

3-Way Control Charts

If the variability within subgroups is very small compared to the subgroup-to-subgroup variability, the limits on the X-bar chart might not be appropriate. You can use 3-way control charts to study both variation ***within*** subgroups and variation ***between*** subgroups.

A 3-way control chart adds a third plot to capture this between-batch variability. This is a plot of the moving ranges between the batches.

Control Charts with Phases

Within the context of problem solving, control charts can be used for a number of reasons throughout the life of a project.

- to determine whether a process is stable,
- to establish a baseline level of performance,
- to explore and analyze patterns of variation in a process, and
- to identify potential problems within a process

They can also be used as follows:

- to determine whether the process has improved, and
- to determine whether improvements are maintained, or sustained, over time

You can add phase variables to calculate the mean and construct control limits for each category of the phase variable.

The Voice of the Customer

Control charts are said to define the *voice of the process*, because control charts help you understand what the process is telling you. Specification limits (or spec limits) are often defined by the customer, so they are sometimes called the *voice of the customer*. We use the term *process capability* to refer to the spread of a stable process relative to the spec limits.

Process capability indices are measures, calculated from data, that compare the spread of the process to the width of spec limits. The most commonly used capability indices are C_p, C_{pl}, C_{pu}, and C_{pk}.

Capability indices are computed as part of a process capability study. In a process capability study, you do the following:

- determine whether the process is stable,
- bring the process to stability (if it is unstable), and
- compute a capability index to quantify the ability of the process to meet customer specifications.

Process Capability Indices

The C_p index is the ratio of the width of the spec limits to the width of the distribution of the process characteristic. C_p does not include information about the center of the process, estimated by X-bar, relative to the spec limits. Because the C_p index assumes that the process is centered, this index is also called the *potential process capability*. It is a measure of what the capability could be if the process were on target.

C_{pl} is used to examine the ability of a process to meet the ***lower spec limit***, and C_{pu} is used to examine the ability to meet the ***upper spec limit***.

C_{pk} is the minimum of C_{pl} and C_{pu}. If the process is perfectly centered within the spec limits, C_p and C_{pk} will be the same. If the center of the distribution is outside the spec limits, C_{pk} will be negative.

If the distribution is perfectly centered and the process spread equals the width of the spec, both C_p and C_{pk} will be 1.0.

- A barely capable process is considered to have a C_{pk} of 1.0.
- Some guidelines require a minimum C_{pk} value of 1.33.
- Some companies require a C_p of at least 2.0 and C_{pk} of at least 1.5.

Short- and Long-Term Estimates of Capability

To compute capability indices, you need to estimate the standard deviation.

- You can calculate a short-term estimate, or
- you can calculate an overall, long-term estimate.

When you use the short-term estimate, the capability indices are labeled C_p and C_{pk}. Because C_{pk} takes into consideration centering, it is sometimes called *actual capability*.

When the long-term estimate of the standard deviation is used, the indices are generally referred to as *process performance indices*. These indices are labeled P_p, for *potential performance*, and P_{pk}, for *actual performance*. The same formulas are used to calculate the process performance indices, but the long-term estimate of the standard deviation is used instead of the short-term estimate.

Understanding Capability for Process Improvement

The capability indices help you understand performance issues.

- If C_p is low, the process has too much variation.
- If C_p is high but C_{pk} is low, the process is off target, but the variability might be acceptable.
- If both C_p and C_{pk} are low, the process is both off target and has too much variability.

Because these indices are based on knowledge of the normal distribution, a capability study also enables you to estimate how much of your product will be out of spec, or nonconforming.

Calculating Capability for Nonnormal Data

For normally distributed data, you know that 99.73% of the observations will fall within +/- 3 standard deviations of the mean. This 6-standard-deviation window defines process spread used to calculate the capability indices. Approximately 0.135% of the observations will be more than 3 standard deviations below the mean, and approximately 0.135% will fall above the mean.

If you use the normal distribution to estimate the percent of measurements out of spec for a nonnormal distribution, you will over- or underestimate the capability of the process. Instead of estimating capability using the normal distribution, you can estimate the capability using the distribution that best fits the data. The same capability indices can be calculated, but indices will be based on the percentiles of the specified distribution.

Estimating Process Capability for Many Variables

Some manufacturing processes have hundreds or even thousands of parameters that are measured and monitored daily. You can compute capability indices for many variables at one time to help you find the poorly performing processes.

It is likely that the different performance measures will have different targets and different spec limits. You can normalize the mean and standard deviation for each variable relative to the specification range. This puts the mean and the standard deviation for all of the variables on the same scale. These normalized values can then be plotted on the same graph, called a goal plot.

If you are on a team improving the performance of this process, the graph helps you identify the variables that are the poorest performers. It also tells you whether you need to address variability, process centering, or both.

Identifying Poorly Performing Processes

Process capability indices, in partnership with control charts on critical process variables, help you identify processes that are performing poorly. Stability is evaluated using control charts. Capability is evaluated based on the ability to meet customer specifications. A capable process must be stable, but a stable process might not be capable. The best processes are both stable and capable.

The stability index and the stability ratio are measures of the stability of the process. The stability index and P_{pk} are plotted on a *process performance graph* to help you understand process stability and performance. The *target index* is a measure of how far off target a process is. The target index measures the number of standard deviations that the mean is from the target.

The stability index, the target index, and the capability indices provide insights into the problems you need to address to improve performance.

- Do you need to stabilize the process?
- Do you need to bring the process to target?
- Or do you need to reduce the common cause variation in your process?

What Is a Measurement Systems Analysis?

When you measure a product characteristic, the total variability that you observe is the sum of the product variability and the measurement variability. For every measurement you take, the measured value is the sum of the actual or true value and the measurement error.

Measurement system studies have two general goals:

- To determine whether the measurement system measures the characteristic of interest accurately, without bias, and
- to determine whether the measurement system is capable of detecting critical differences in the characteristic. This is a function of the variability, or the precision, of the measurement system.

Language and Terminology

There are five characteristics of a measurement system that can be studied in an MSA.

Repeatability is the variability in repeated measurements of the given characteristic with the same operator, same gauge, same location, and the same part. *Reproducibility* is the variability introduced by different operators using the same gauge to measure a given characteristic on the same part. Repeatability and reproducibility together describe the *precision* of the measurement system relative to the specification limits.

Stability is the consistency of the measurement system over time. *Bias* is the difference between the measurement and the true (or reference) value, and *linearity* is the absence of bias across the operating range of the measurement system.

The ideal measurement system

- is stable,
- is accurate, or unbiased, and
- is precise, or has little variability relative to the spec limits.

Designing and Conducting an MSA

During the measurement study, you use gauge study worksheets to organize the presentation of objects to inspectors (or operators), and to enter the measured values. A selection of parts that spans the operating range is used for the study. The parts are presented to the operators in random order to prevent the operators from remembering the previous measured value. Measuring the same object more than once gives you the ability to estimate the repeatability variation in the measurement system.

It is recommended that you conduct the MSA in a blind fashion. This means that you have the inspectors measure each part without the other inspectors observing the process or hearing the measurements. This reduces the chance that an inspector will be influenced or biased by other inspectors.

As you conduct the MSA, you might observe differences between inspectors as they are taking the measurements. You want to take notes during the MSA and record these observations. The differences you note might be causes of variation in the measurements, and these insights can lead to improving the performance of the measurement system.

Analyzing an MSA with Visualizations

As with all good analyses, you should start by visualizing the data before conducting a formal analysis.

A variability chart, or multi-vari chart, shows each combination of the factors in our MSA. The variability chart enables you to visualize repeatability variation, reproducibility, and interactions.

Another way to visualize the data is with average and range control charts, or average and standard deviation control charts. The range chart enables you to see whether the repeatability variation for each part is consistent across the inspectors.

You interpret the average control chart differently than you interpret the standard control chart. In an MSA, you ***want*** the average chart to be out of control! If the variability for repeated readings is small, the control limits for the average chart will be very tight and many of the points will fall outside the limits. If most or all of the points fall outside the limits on the average chart, this means that you can tell the difference between the parts.

Another useful visualization is a parallelism plot. In this graph, if the lines are parallel, then each Inspector is getting approximately the same measurements for each part. This means that there is no interaction between the parts and the inspectors.

Analyzing the MSA

You can use a variety of statistical methods to formally analyze and quantify measurement system variation. One popular method is a *variance components analysis*. Variance components are estimates of the variation attributed to each component, or source, of measurement system variation.

You can use the variance components to compute the measurement process width. This is the range of potential values directly attributed to the measurement system.

One way of looking at the variance components is to combine the terms attributed to gauge repeatability and reproducibility. Gauge R&R is a stand-alone method for analyzing the repeatability and reproducibility in a measurement system. (This method is discussed in a JMP Demo.)

Studying Measurement System Accuracy

A measurement system can be repeatable and reproducible, but this does not mean that the measurement system can accurately measure the parts. Bias is the difference between the measurement and the true value. A biased measurement system is, on average, not accurate.

In order to estimate the bias, you must know the true value of each item being measured.

We call this true value the s*tandard*. Comparing the measured value to the standard enables you to study the bias in the measurement system.