

STATISTICAL PROCESS CONTROL (SPC) GUIDE LINE

Vivek Singh
Quality Manager, India

Abstract: Statistical process control (SPC) is a method of quality control which employs statistical methods to monitor and control a process. This paper helps us to ensure that the process operates efficiently, producing more specification-conforming products with less waste. SPC can be applied to any process where the "conforming product" output can be measured. Key tools used in SPC include run charts, control charts, a focus on continuous improvement. An example of a process where SPC is applied is in manufacturing lines.

Key Word: Statistical process control, control charts, Methodology, rules

I. INTRODUCTION

SPC has been around since the early 1920s. It involves the study of **variation**, which simply means difference. Variation is referred to as either **common** cause, which is inherent variation (often called noise), or **special** cause, meaning there's an assignable reason for its occurrence. Special cause variation results from circumstances that are not always acting on the process, but when they are, instability will affect the output until they are identified and addressed. The purpose of SPC is to cost effectively ensure that products produced meet the customer's expectations. From a "system" standpoint, it defines the extent of common cause variation and also signals when a special cause has acted on it so that its source can be identified and reacted to before the problems arise.

Pre-Requisites

There are three key necessities for the application of SPC: measurement system robustness; a sample data collection scheme; and the ability to react to special cause instability, if encountered, in real time. Each will be covered at an introductory level below. More detailed information can be found in the SPC.

Measurement System Robustness

A critical issue in preparing to implement SPC is that no measurement system is without variation. The broad topic is referred to as Measurement System Analysis. Measurement system robustness is defined as the system's ability to minimize variation from measurement practices, therefore providing a consistent means of acquiring accurate and precise data for the feature to be checked. In other words, by

using the best-suited device, providing details and documented instructions and thoroughly training all those who will collect data

Abbreviations and Acronyms

SPC Statistical Process Control, CMMs Co-ordinate Measuring Machine, 5M&M Man, Machine, Material, Method, Movement, Environment, SPM Statistical Process Monitoring, LCL Lower Control Limits, UCL Upper Control Limits, CMM Capability Maturity Model, CMMI Capability Maturity Model Integration, HML Hypertext Mark-up Language, HCM Hardware Compatibility List.

The most common control chart types for variable and attribute data

There are different kinds of control charts for variable and attribute data. That said, they generally share a common look and features:

- Each studies a specific characteristic of a part or process (vertical axis) over time (horizontal axis).
- Data points are plotted in a graphical framework.
- Analysis is conducted with respect to an average line and control limits (**not specification limits**).

Chart -1: Control Charts

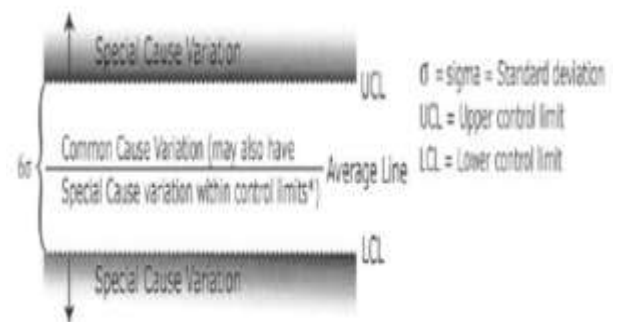


Fig -1: Control Charts Characteristics

Control limits are the boundaries of a zone in which almost all the data should fall in order for the process to be in a controlled state. **The key point for control charts is the ability to separate special (assignable) cause variation**

from common (inherent) cause variation, allowing for correction before the production of non-conforming product.

Types of Charts

There are two types of data are commonly use in SPC

- 1) Variable Data
- 2) Attribute Data

Variable Data Charts:-

X-Bar and R-Bar Chart

When it comes to variable data, the overwhelmingly preferred control chart type is the \bar{x} (read as X-bar) and R. (An example is shown below.)

These are often referred to as “average & range” (or Shewhart) charts. They are favored because:

- Calculations are relatively easy.
- Underlying distribution of individuals need not be normal. They are less susceptible to type 1 errors (over adjustment/adjusting when not necessary).
- Why? Because the averages of the average tend toward normality.

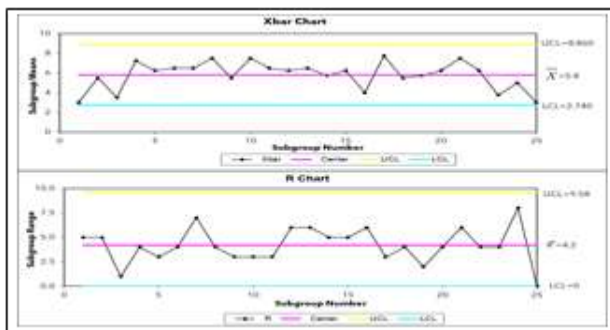


Fig -2: X-Bar and R-Bar Chart

How to use it

For the studied characteristic:

- i. Subgroups are formed from a constant number of samples gathered in succession.
- ii. To calculate the average of the subgroup, add these sample values together, and divide the sum by the total number of samples.
- iii. Plot that results on the X-bar chart.
- iv. To determine the range of the subgroup, subtract the smallest value from the largest.
- v. Plot that results on the R Chart.
- vi. Log any information that relates to possible process effects.

This activity is repeated on a regular frequency (e.g., once an hour, twice a shift etc.)

Individuals and Moving Range (I & MR) Charts

Another popular variable data control chart type is the individuals and moving range chart (I and MR). (An example is shown following.)

On the plus side

- Calculations are very easy with a subgroup size of 1 (none at all on the Individuals chart, and only subtraction of two numbers on the MR charts)
- If offers a way to statistically control a process where samples are scarce or costly to evaluate, or samples are produced in homogeneous batches where repeated sampling within the batch would not vary (e.g., chemicals etc.)

On the minus side

- With a sample size of 1, there is increased susceptibility to type 1 errors because, unless the under laying data are “somewhat” normally distributed, the Individuals Chart will give more false signals for certain tests of stability (indicate that the process is out of control when it actually is not), and
- Because of its subgroups size 1, I and MR control charts are not sensitive to shifts in the means of the process as X-bar and R charts. Generally speaking, the larger the subgroup size, the more sensitive it is to those types of changes.

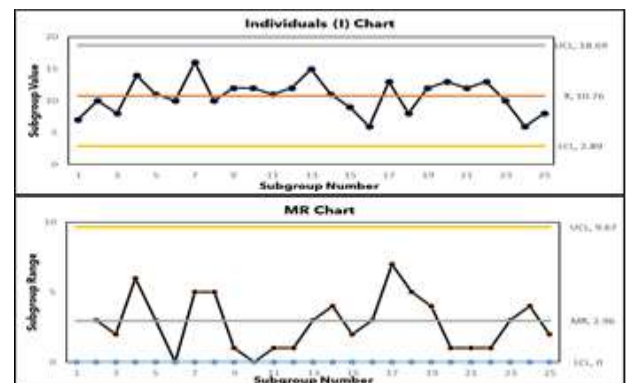


Fig -3: I and MR Chart

How to use it

One Sample is selected for the studied characteristic:

- i. Plot its value on the Individuals chart.
- ii. Calculate the moving range by subtracting the last two samples from each other and taking the absolute value of the result. There will always be one less MR value than the Individuals value because of this method.
- iii. Plot that number on the MR chart



This activity is repeated on a frequency that coincides with the availability of sample data (e.g., once a shift, once a day, etc.).

Attribute Data Charts:-

Control charting for attribute data is similar in format to that for variable data; however, there are some structural differences:

- Remember, attribute data is counting (or discrete) data.
- Unlike control charting for variable data, there is no R chart for attribute data.
- Also, there is not one prevalent chart type for attribute data as there is for variable data (X-bar & R Charts).
- Because attribute data are less “powerful” than variable data, attribute data require much larger sample size to reap similar benefits

The diagram below shows the four commonly used chart types for attribute data. The proper one to apply in a particular circumstance is based on answering two questions:

- i. Are subgroup sizes constant?
- ii. Is the characteristic being studied described as a defect or a defective?

	Defects	Defectives
Variable Sample Size	U - CHART	P - CHART
Constant Sample Size	C - CHART	NP - CHART

A defect is a failure to meet a single requirement.
 A defective is a unit containing 1 or more defects.

Control Charts for Defectives: P and NP

P and NP charts show how the number of defective units changes over time. Examples are paint aberrations on a completed vehicle and fabric irregularities in a bolt of cloth. These two charts are essentially the same, except that a P chart does not require a constant sample size while an NP chart does

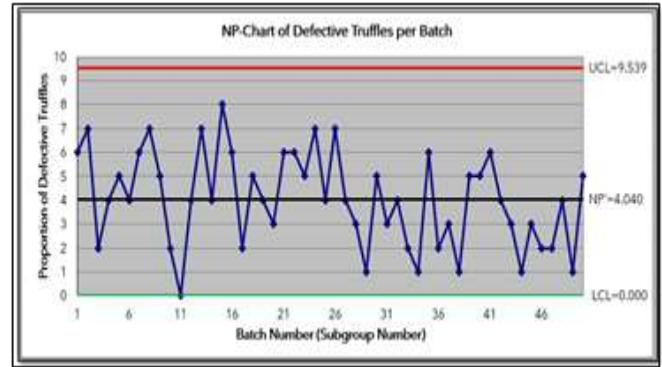


Fig -4: P Chart

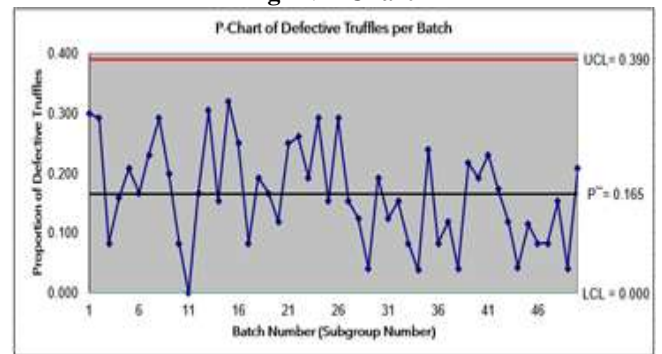


Fig -5: NP Chart

How to use P Chart

Define a unit, It should be a logical selection like a car, purchase order, sheet of raw material, etc.

- i. Identify the defects that could affect a unit.
- ii. Determine how many units will constitute a subgroup. Again, the choice should be logical, e.g., number of units completed in a period of time (hour, shift, day, etc.).
- iii. For each subgroup, calculate the percent defective by dividing the number of defective units by the total number of units. Plot this value on the P chart.
- iv. To maintain constant control limits for the P chart, keep the ratio of the min to max subgroup size ≥ 0.75 . In cases where you cannot keep the ratio of the min to max subgroup size ≥ 0.75 , calculate the control limits specifically for those subgroups.
- v. Anytime a violation of the min to max subgroup ratio occurs after the control limits have been calculated, calculate and use the control limits for that specific subgroup.

How to use NP Chart

- I. Since both the P and NP Charts defective units, they function in much the same manner. Because the subgroup sample size must remain constant for an NP chart, the actual defective count is plotted for each



subgroup as opposed to the ratio of defectives over sample size

Control Charts for Defectives: C and U

U and C charts show how the number of defects per unit(s) changes over time. Defects can be described as any characteristic that is present but should not be, or not present but should be. For example, a scratch, contaminant, missing item, and extra item are all defects.

These two charts are essentially the same, except that a U chart does not require a constant sample size per subgroup, whereas the C Chart does.

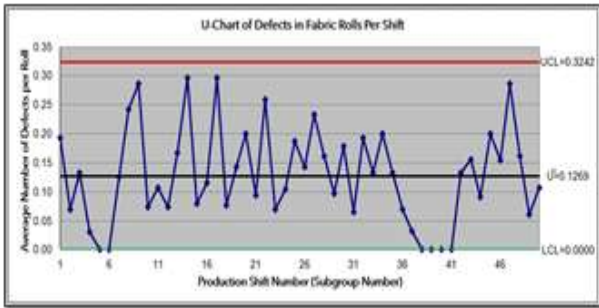


Fig -6: U Chart

How to use C Chart

- i. First, describe the potential defect(s).
- ii. Identify what constitutes a subgroup (usually the number of units within a time frame, e.g., work shift, etc.).
- iii. For each subgroup, calculate the average number of defects by dividing the number of defects by the total number of units. This value is plotted on the U Chart.
- iv. To maintain constant control limits for the U chart, keep the ratio of the min to max subgroup size ≥ 0.75 . In cases where you cannot keep the ratio of the min to max subgroup size ≥ 0.75 , calculate the control limits specifically for those subgroups.
- v. Anytime a violation of the min to max subgroup ratio occurs after the control limits have been calculated, calculate and use the control limits for that specific subgroup.



Fig -6: C Chart

How to use C Chart

Since both the C and U Charts monitor defects, they function in much the same manner. Because the subgroup sample size must remain constant for a C Chart, the actual defect count is plotted for each subgroup as opposed to the ratio of defects over sample size.

Rules of abnormal condition of SPC :-

Rule 1:- One point is more than 3 standard deviations from the mean. One point is outside the control limits as shown in fig 7.

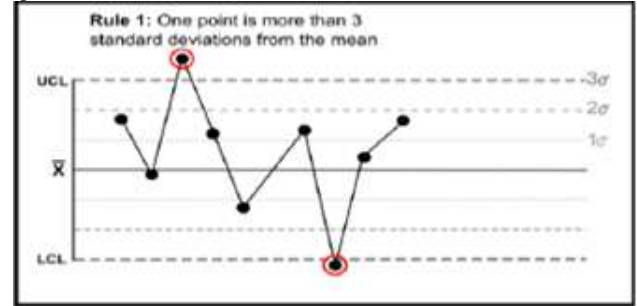


Fig -7: SPC Chart for Rule 1

Rule 2:- Nine (or more) points in a row are on the same side of the mean. This represents sudden, large shifts from the average. These are often fleeting – a one-time occurrence of a special cause – like the flat tire when driving to work as shown in fig 8.

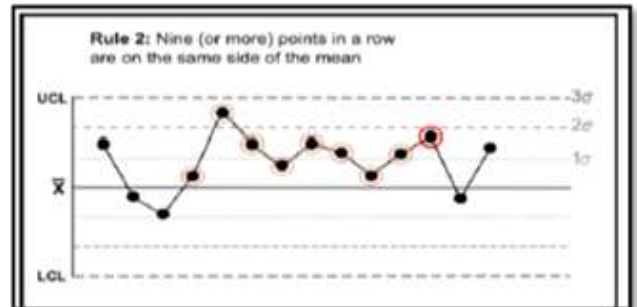


Fig -8: SPC Chart for Rule 2

Rule 3:- Six (or more) points in a row are continually increasing (or decreasing) trend exist either moving to upper limit or lower limit as shown in fig 9.

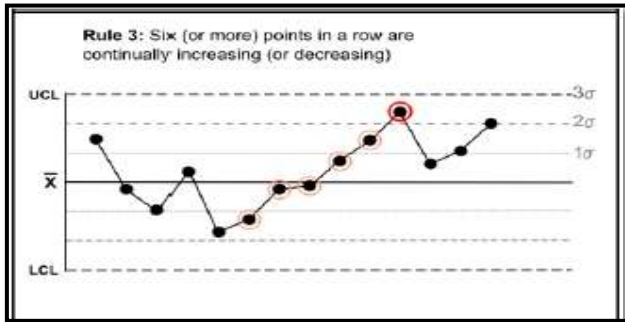


Fig -9: SPC Chart for Rule 3

Rule 4:- Fourteen (or more) points in a row alternate in direction, increasing then decreasing. They represent smaller shifts that are maintained over time. A change in raw material could cause these smaller shifts as shown in fig 10.

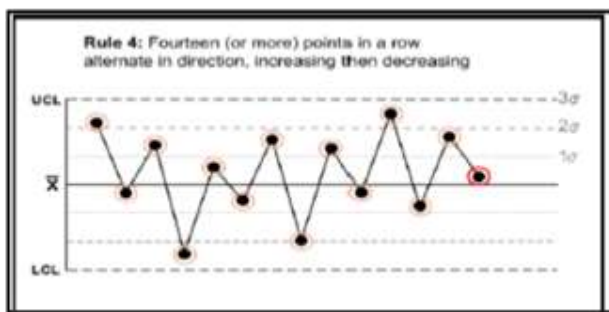


Fig -10: SPC Chart for Rule 4

Rule 5:- Two (or three) out of three points in a row are more than 2 standard deviations from the mean in the same direction. This represents a process that is trending in one direction. For example, tool wearing could cause this type of trend. This is shown in fig 11.

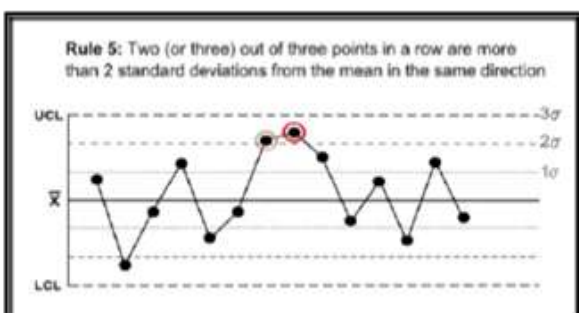


Fig -11: SPC Chart for Rule 5

Rule 6:- Four (or five) out of five points in a row are more than 1 standard deviation from the mean in the same direction. It occurs when you have more than one process present and are sampling each process by itself. This is shown in fig 12.

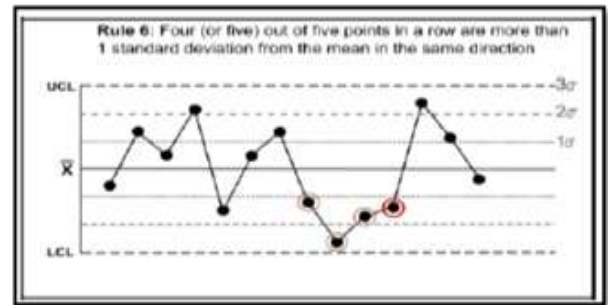


Fig -12: SPC Chart for Rule 6

Rule 7:- Fifteen points in a row are all within 1 standard deviation of the mean on either side of the mean. Rule 7(stratification) also occurs when you have multiple processes, but you are including all the processes in a subgroup. This can lead to the data “hugging” the average. This is shown in fig 13.

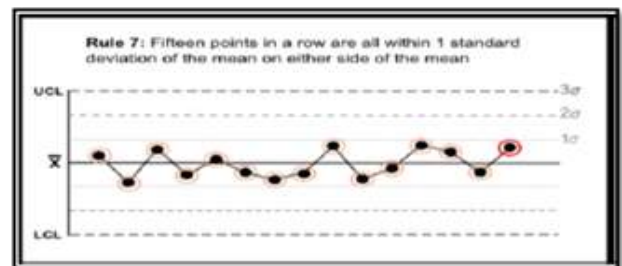


Fig -13: SPC Chart for Rule 7

Rule 8:- Eight points in a row exist with none within 1 standard deviation of the mean and the points are in both directions from the mean. Rule 8 (over-control) is often due to over adjustment as shown in fig 14.

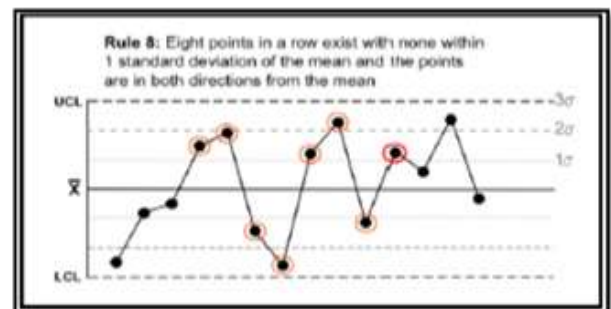


Fig -14: SPC Chart for Rule 8

Application of SPC:- SPC is used in manufacturing industries to understand the process and the specification limits. Eliminate special cause of variation, so that the process is stable. Monitor the on-going production process, assisted using control charts, to detect significant changes of mean or variation.

Steps of SPC:- There are 07 steps to set up Statistical Process Control (SPC) on Production process. This is shown in Fig 15.



Fig -15: Steps of SPC

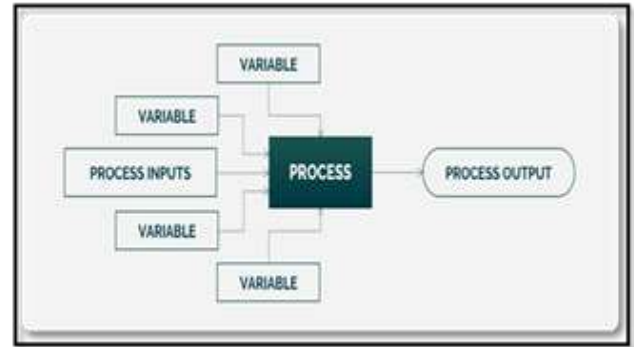
1) Select critical- to- quality (CTQ) products characteristics:- For example, if metal thickness is lower than specification then it might not perform its task. Thickness is CTQ characteristics.

2) Select critical processes:- What qualifies a process as “critical”? If something goes wrong with that process, it will probably have a sizable impact on at least one CTQ characteristic. Critical processes are often indicated with a ‘*’ on the control plan

3) Determine if machines can calculate SPC by themselves:- Many modern pieces of equipment collect and analyze data, and then issue an alert when they get out of control. However, this is very uncommon in industry, so let’s assume this is not the case; it means you will need to carry out steps 4 and 5

4) Gather data and process knowledge of what impacts the output of the process:- For example, the variables that might affect the output of a gluing process are listed below:

- Process input: glue
- Process settings: cycle time; fixture
- Environment: outside temperature, humidity, etc.

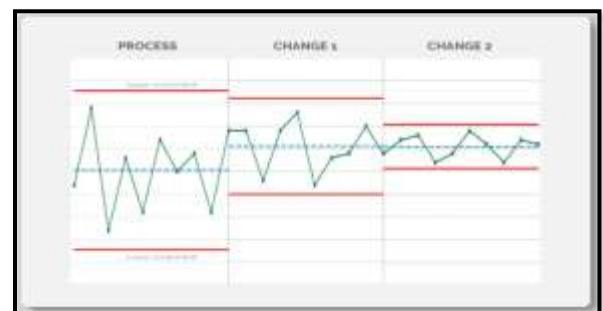


Based on this, you might conclude that the viscosity of the glue and the ambient humidity are two variables that need controlling.

5) Control independent variables that have a sizeable impact on the process output:- There are 2 ways you can ensure that your production does not deviate too much:

- 1) Gather data on the variables you identified previously on a regular basis, e.g., 5 random samples every 4 hours.
- 2) Teach the production operators and leaders necessary calculations and how to plot them on a chart, e.g., on the “X bar – R” chart, the most popular tool. For simplicity, we tend to set a goal for the process capability index (Cpk) and let operators plot the evolution of that index over time.

6) Look for ways to reduce variation:- Now that you have made variations visible, the next step is to find ways to reduce it. If you use statistical process control charts, ideally it looks somewhat like this:



As long as the Cpk index is within the control limits, engineers and production leaders are encouraged to test different approaches. A Cpk target of 1.0 is often attainable within a few weeks. 1.33 is more challenging. 1.66 is much, much harder!

If necessary, you can use another statistical technique called Design of Experiments (DoE) to help you get close to the optimal values for variables that impact your process output. But, be prepared – there are several available approaches here, and it can get relatively complex.



7) Keep it up in the long term: - You manage to reduce variation. Set a new target and keep controlling the key variables. If your process characteristics drift in one way or another, your statistical process control system will alert you. Otherwise, don't tamper with the process, constant little adjustments will mechanically make the process "unstable" in statistical terms.

Single Process Study vs. Process Capability Assessment: A Frequency Used Approach
 While the approach described below frequency occurs, **this is not the preferred approach.**

Typically, during the first trial run of the new process, parts are collected from the run and a process capability assessment is conducted using the collection data. The samples are randomly selected without any sub grouping. The following example is based on randomly selecting 30 pieces from 100-piece trial production runs. In reality, the total number of pieces produced and sampled will be depend on factors such as customer requirements, ordered quantity, production time allotment, etc.

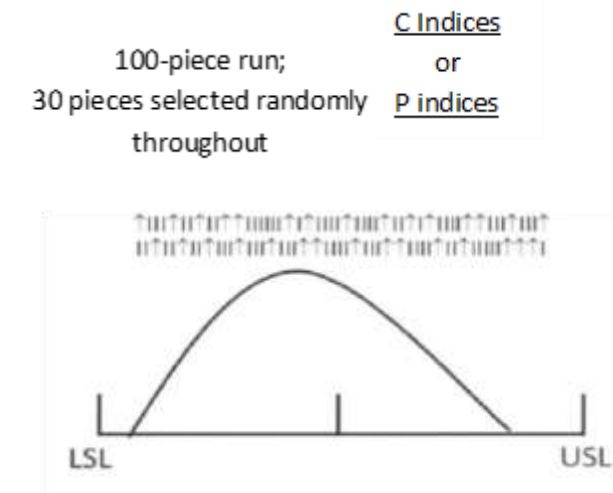


Fig -16: PPE 1 Frequency Used Approach

$CR = \frac{6\sigma}{USL - LSL} \quad \sigma = \frac{\bar{R}}{d_2}$	$PR = \frac{6\bar{x}}{USL - LSL} \quad \sigma_S = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{(n-1)}}$ <p>$n = \text{Subgroup Size}$</p>
---	---

CR = Capability Ratio
 PR = Performance ratio

During the next PPE, the samples are again collected randomly and capability is inappropriately calculated

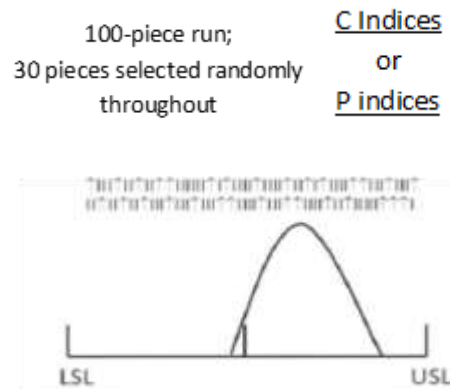


Fig -17: PPE 2 Frequency Used Approach

This approach continues during subsequent PPEs. These individual activities are inappropriately referred to as SPC.

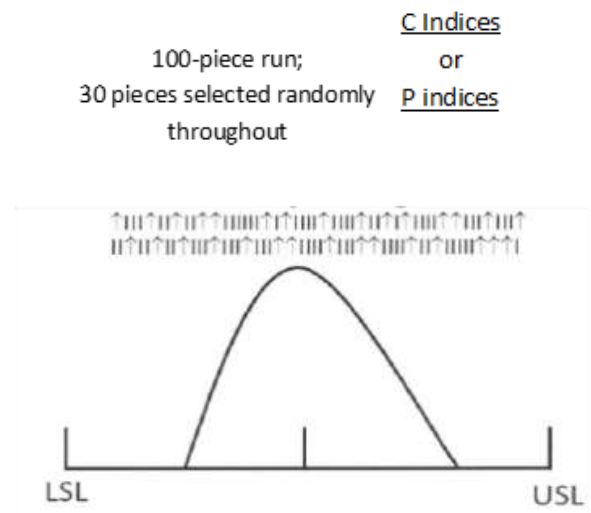


Fig -18: PPE 3 Frequency Used Approach

Process Improvement through Nominal Targeting and/or Variation Reduction
First & Foremost, No Discussion About Process Improvement Should Take Place For An Unstable Process!

For variable data, when enough data have been collected to satisfactorily estimate the standard deviation from the control chart subgroups ($\bar{R} - \bar{\sigma}/d_2$), both Cpk and Ppk can be calculated. For further information on calculating capability index as per given below. Be sure to consult with customer(s) for their specific capability requirements, but the typical acceptable value is **1.33**. This is equivalent to $\pm 4\sigma$ (8 total standard deviations) laying within the tolerance. The larger the numbers, the better!



Zmin is calculated as per given below.

➤ For a unilateral tolerance, calculate: $Z = \frac{USL - \bar{x}}{\sigma_{\bar{R}}/d_2}$ or

$Z = \frac{\bar{x} - LSL}{\sigma_{\bar{R}}/d_2}$, whichever is appropriate

Where SL = specification limit, \bar{x} = measured process average and $\sigma_{\bar{R}}/d_2$ = estimated process standard deviation

➤ For bilateral tolerances, calculate:

$$Z_{USL} = \frac{USL - \bar{x}}{\sigma_{\bar{R}}/d_2} \quad Z_{LSL} = \frac{\bar{x} - LSL}{\sigma_{\bar{R}}/d_2}$$

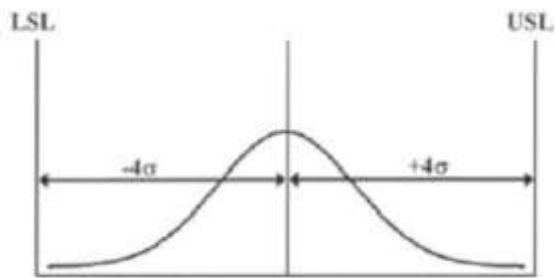
Zmin = Minimum of ZUSL or ZLSL

where USL, LSL = upper and lower specification limits; a negative value of Z indicates the process average is out of specification.

The value Zmin can also be converted to Capability Index, Cpk, defined as:

$$Cpk = Zmin/3 = \text{Minimum of CPU} \left\{ \text{i.e., } \frac{USL - \bar{x}}{3\sigma_{\bar{R}}/d_2} \right\} \quad \text{or}$$

$$\left\{ \text{CPL} \quad \text{i.e., } \frac{\bar{x} - LSL}{\sigma_{\bar{R}}/d_2} \right\}$$



Assuming Cp = Cpk

Fig -19: Normal Distribution with Capability Associated with PPM

Sigma #	Cpk	% within Tolerance	Parts per Million
1	0.33	68	3,20,000
2	0.67	95	50,000
3	1.00	99.73	2700
4	1.33	99.9937	63
5	1.67	99.99994	1
6	2.00	99.9999998	2 per Billion

Note:- The 3.4 ppm goal of Six Sigma Strategy is a Cp = 2.0 and Cpk = 1.5

For the attribute side, things are much easier regarding computation of capability. As an example, assume a P chart with P-bar (average) at 0.27%. Simply subtract that from 100% to get a capability index of 99.73%, which is the equivalent to +/- 3s capability.

Corrective actions for incapable processes come down to two directions: If Pp or Cp is acceptable but Ppk or Cpk is not, Approach 1 is applicable (see Figure 23). If Pp or Cp is not acceptable, then Approach 2 is necessary (see Figure 21).

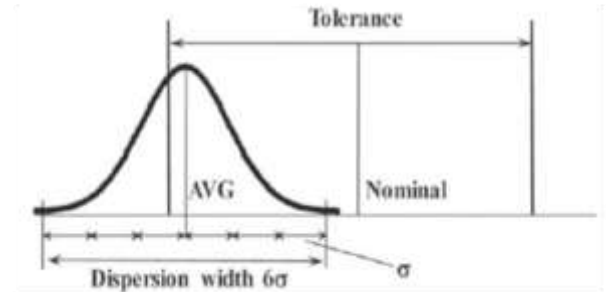


Fig -20: Approach 1 Center the Process at the Target (nominal) Value

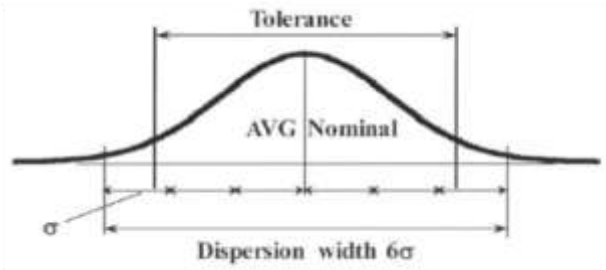


Fig -21: Approach 2 Center the Process at the Target (nominal) Value



In some instances, reducing the variation alone (i.e., getting Pp and Cp to an acceptable value) will not make the process capable. It will be apparent when Ppk and Cpk are calculated that both approaches are required.

It is usually easier to center a process than to reduce its variation (due to the number of factors and time involved). If presented with a choice, always opt for centering first.

Changing Conditions/Reallocating Resources

Studied characteristics that exhibit stability for an extended period of time into volume production, with capability indices exceeding customer requirements, are candidates for SPC reflection. Reflection in this sense typically means assessment of the continued return on investment (ROI). Can the process/product under statistical control continue to be improved economically, or will you be spending a dollar more to save an additional dime? Doing SPC for the sake of doing SPC can erode the foundation of a well-intentioned quality plan. Of course, if the characteristic being controlled is mandated by the customer, the above question should not be answered without their input. If after reviewing the evidence they are unwilling to remove or reassign the requirement outright, check to see if they are open to a reduced sampling frequency or some other alternate approach for ensuring quality.

II. CONCLUSION

After verification of Statistical Process Control, following points are observed.

Control Charts that help monitor manufacturing processes can be more helpful digitally as they can be presented by a well-designed system.

Data for monitoring and visualization is better through applications as all data and visualization for it is accessible easily.

Customization to system and any addition to Statistical Process Control is easier as systems can be reprogrammed to add functionalities necessary, without excessive usage and analysis training Provision of other charts that could be useful such as normality charts and mean charts.

III. REFERENCES

- [1]. Barlow, R. E. & Irony, T. Z. (1992) "Foundations of statistical quality control" in Ghosh, M. & Pathak, P.K. (eds.) Current Issues in Statistical Inference: Essays in Honor of D. Basu, Hayward, CA: Institute of Mathematical Statistics, 99-112
- [2]. Salacinski, T (2015) SPC - Statistical Process Control. The Warsaw University of Technology Publishing House.
- [3]. S. Jagannatha, M. Niranjanamurthy, and P. Dayananda, "Algorithm Approach: Modelling and Performance Analysis of Software System", Journal of Computational and Theoretical Nanoscience

(American Scientific publishers), December 2018, Volume 15, Issue 15, PP. 3389–3397.

[4]. AIAG Manual- Fourth Revision