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Enhancing Manufacturing Quality Through Statistical Process Control

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Abstract - In the manufacturing industry, statistical process control, often known as SPC, is a strong instrument that can improve both the quality of the product and the efficiency of the process. It comprises the utilization of statistical approaches for the purpose of monitoring and controlling a process in order to guarantee that it functions effectively and generates products that are of a consistently high grade. The statistical process control (SPC) method enables producers to identify variances, trends, and irregularities that may have an impact on product quality. This is accomplished by collecting and analyzing data from the production process. It is possible for manufacturers to discover and rectify problems in real time with the assistance of statistical process control (SPC), which is accomplished through the utilization of control charts, process capability analysis, and other statistical approaches. This results in decreased waste, greater productivity, and increased customer satisfaction. This article examines the fundamentals of statistical process control (SPC), as well as its application in manufacturing environments and the advantages it offers in terms of improving both product quality and process performance.

Keywords: Manufacturing, Quality, SPC

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INTRODUCTION

When it comes to the manufacturing industry of today, which is extremely competitive, maintaining product quality is of the utmost importance for the success of any organization. Not only does poor quality result in dissatisfied customers, but it also results in considerable expenditures owing to the need for rework, scrap, and warranty claims. Manufacturing companies utilize a wide range of quality management strategies in order to handle these difficulties. Statistical Process Control (SPC) stands out as one of the most successful methodologies among these manufacturing strategies. Statistical Process regulate (SPC) is a methodology that has its origins in statistical analysis and provides businesses with the ability to regularly monitor and regulate production processes. It is possible to spot variances and irregularities that might lead to defects or deviations from expected quality standards with the use of statistical process control (SPC), which involves continually collecting and evaluating data from the production line. This proactive strategy enables manufacturers to respond swiftly, so guaranteeing that processes continue to operate within the control limits that have been defined and that goods are produced that are continuously of high quality. The ideas, methodology, and advantages of statistical process control (SPC) in industrial environments are investigated in depth in this study. We investigate the ways in which statistical process control (SPC) enables businesses to achieve improved process stability, reduce the number of errors, maximize the usage of resources, and ultimately improve customer satisfaction. We also examine the practical concerns that need to be taken into account when adopting SPC systems. These include the collecting of data, the methodologies for analysis, and the connection with quality management frameworks that are already in place. The purpose of this article is to give manufacturers with useful insights into harnessing statistical techniques to drive continuous improvement and elevate manufacturing quality to new heights. This will be accomplished via a detailed review of statistical process control (SPC).

OBJECTIVES

1. The research aims to examine how well statistical methods are used for birth defect surveillance.

2. To study how to use multivariate control charts to monitor process performance, look into control chart construction using the direct fuzzy approach.

Statistical Control Charts for Variables

The term "variable" may be described as any sort of measurement for quality in the field of industrial statistics, which is where quality qualities are given in numerical measures. This includes, but is not limited to, weight, volume, size, and other similar measurements. A approach that is utilized extensively throughout the sector is one that involves controlling the mean as well as the variance of the quality feature.

Examples of variable control charts include:

(i) Chart: These charts are associated with control in accordance with the mean or average quality requirements of the control process. The development of this chart begins with the collecting of samples of the process at a variety of intervals. Next, the mean of each sample is calculated, and then the mean is plotted on the chart. Finally, the chart is constructed. One may determine whether or not the mean output of the process has changed over the course of time by using this chart to identify the difference between the real process mean and the notional process mean. Another way to utilize this information is to determine whether or not the process has changed.

(ii) R (Range) Control Charts: There is a connection between these charts and sample sizes that are often thought to be on the smaller side. It is clear from this that there is a wide range of possibilities during the procedure. The difference between the lowest and highest values for each data set is recorded and shown, with the centerline being the average of all ranges. This difference is displayed. This graphic is utilized in the process of data analysis.

(iii) S Charts: which are sometimes referred to as Standard Deviation Charts, are charts that, in contrast to the R-Charts that were mentioned before, deal with extremely large sample sizes of data. All of the sample data is taken into consideration by the S-chart, which also takes into account the maximum and lowest conceivable values and their respective values.

Statistical Control Charts for Attributes

In situations when quality characteristics cannot be measured mathematically, attributes control charts are an extremely helpful tool to have at your disposal. Within the scope of this discussion, some examples of common characteristics are conforming or nonconforming units, defective or nondirective units, and conventional or nonconforming units. The following are some examples of control charts that are used for attributes:

(i) C (Count) Charts: these charts deal with the number of defects per unit sample. Here the number of samples per sampling period remains constant in this case.

(ii) U (Unit) Charts: these charts are similar to C charts, though the only difference is that the number of samples per sampling varies over a period of time.

(iii) P (Proportion) Charts: these charts deal with fractions or proportions of defects and shows if the defect changes over a period of time and the size of a p chart varies.

In addition to this, there are also pre-control charts and np charts associated with attribute control. Not only are np charts comparable to P-charts, but the main distinction between the two is that np charts display the number of faults rather than the % of defects across the sample time. Pre-control charts are utilized for the purpose of comparing individual analyses to the standards that are permissible.

According to Montgomery (2004), The following are some of the reasons why control charts have become increasingly popular:

They are a justifiable approach to quality improvement.

1. Defects are effectively avoided or reduced with their help.
2. They save time and money by avoiding unnecessary process modifications.
3. They reveal details about a process's performance capabilities.

ACCEPTANCE SAMPLING PLANS

Depending on whether or not it satisfies the quality standards that are linked between them, this is a method that involves approving or rejecting a significant amount of anything. Control charts are employed during the manufacturing process, whereas Acceptance Sampling is performed after the product has been made. This is done in order to separate itself from Statistical Process Control, which is applied throughout the production process. For the purposes of this application, the focus is on a large number of comparable items that have already been made or are in the process of being transferred from one site to another. Similar to control charts, acceptance sampling plans may be separated into two unique forms: acceptance sampling by variables and acceptance sampling by characteristics. Both of these types of plans represent acceptance sampling. Acceptance sampling is a term that is used to describe both of these different sorts of programs.

Acceptance Sampling by Variables

Within the field of modern statistics, acceptance sampling is regarded as a subject that is believed to be exciting. Once the quality measures have been developed and the quality characteristics have been established, it is feasible to measure an item rather than classifying it as conforming or non-conforming. This is because it is possible to measure an item. The thickness, weight, or even strength of an object is measured in this scenario, and it is assumed that the item follows the normal distribution. For example, the thickness of the object may be measured. The Acceptance Sampling by Variables technique includes picking a sample at random from a batch, and then determining the sample's mean value after the sample has been selected. The batches are then analyzed to see whether or not they meet the criteria by evaluating whether or not this average is greater than the acceptance number. This may be done by comparing the acceptance number to the average.

Acceptance Sampling by Attributes

The testing procedure assigns a conforming or nonconforming characteristic to each and every item that is placed through the process. This is similar to how control charts are constructed. A fraction of a batch is selected for testing, and if the sample in question contains a considerable number of goods that do not match to the requirements, the entire batch is destroyed. This sample is picked for testing. Due to the fact that doing so would not be efficient, it would not be cost-effective to throw out all of the items that are included in a batch when employing the Acceptance Sampling by Attributes approach. Therefore, in order for this technique to be successful, it is essential to determine a specific percentage of goods that do not adhere to the standards. These ranges determine whether or not the non-conforming products are approved; if they do not fall within these limits, then they are being rejected. There is the possibility of constructing an extra categorization of acceptance sampling procedures according to the categories that are listed below:

1) The first method, called the "single sampling plan," involves selecting a random number n from a pool of N samples and comparing it to a predetermined acceptability number c and the number of faults d. If there are fewer flaws (d) than the acceptance number (c), then the batch can be regarded acceptable. If not, it will be rejected.

2) The Double-Sample Plan: This plan is an expansion of the previous single-Sample Plan; however, it has two trials instead of one, which entirely eliminates the potential of error.

3) The third type, called a multiple sampling strategy, involves doing a plethora of tests until a definitive verdict is reached.

4) Sequential sampling is the fourth kind of inspection plan. In this method, each item is checked one by one, and the inclusion or exclusion of each item is decided independently by using the sample size as a random variable.

In addition to this kind of traditional technique, the Bayesian methodology was also utilized in the process of developing the procedures for quality control. A discussion of the Bayesian technique is presented in the following.

RESULTS

In order to accomplish the goals of this article, the current investigation has been carried out to investigate the procedure that is used to manufacture paper. According to the conclusions reached by the specialists, the quality of the document may be classified into four distinct categories: standard, first preference, second preference, and useless.

Traditional p Control Chart

The values of the Shewhart p control chart, including the UCL, LCL, CL, and p values, are calculated and shown in the table under consideration:

Table 1: Results of traditional p control chart

Sample	p	LCL	UCL	CL
1	0.08	0	0.49	0.232
2	0.04	0	0.49	0.232
3	0.16	0	0.49	0.232
4	0.24	0	0.49	0.232
5	0.16	0	0.49	0.232
6	0.28	0	0.49	0.232
7	0.36	0	0.49	0.232
8	0.12	0	0.49	0.232
9	0.28	0	0.49	0.232
10	0.44	0	0.49	0.232
11	0.16	0	0.49	0.232
12	0.28	0	0.49	0.232
13	0.2	0	0.49	0.232
14	0.32	0	0.49	0.232
15	0.16	0	0.49	0.232

16	0.24	0	0.49	0.232
17	0.2	0	0.49	0.232
18	0.12	0	0.49	0.232
19	0.48	0	0.49	0.232
20	0.4	0	0.49	0.232
21	0.28	0	0.49	0.232
22	0.24	0	0.49	0.232
23	0.12	0	0.49	0.232
24	0.28	0	0.49	0.232
25	0.08	0	0.49	0.232
26	0.16	0	0.49	0.232
27	0.08	0	0.49	0.232
28	0.44	0	0.49	0.232
29	0.24	0	0.49	0.232
30	0.32	0	0.49	0.232

Fuzzy p Control Chart

Each and every linguistic word is associated with a fuzzy subset, and a membership function is used to define such associations. In order to do transformation, we make advantage of fuzzy mode. According to our findings, the following linguistic concepts have representational values:

Standard = 0 1st Preferences = 0.25

2nd Preferences = 0.5 Useless = 1

The value of inspection tightness α is assumed as α = 0.50. Then the Control limits are:

Left Hand Side Portion:

LCL = 0 CL = 0.1878 UCL = 0.4222

Right Hand Side Portion:

LCL = 0.4098 CL = 0.6878 UCL = 0.9658

For 0.70= ŧ, the control limits are:

Left Hand Side Portion:

LCL = 0 CL = 0.2629 UCL = 0.5271

Right Hand Side Portion:

LCL = 0.2624 CL = 0.5629 UCL = 0.8606

For α=90, the control limits are:

Left Hand Side Portion:

LCL = 0.0543 CL = 0.3381 UCL=0.6219

Right Hand Side Portion:

LCL =0.1404 CL = 0.4381 UCL=0.7358

Table 2: Results of applying fuzzy approach (0.50=ŧ)

Samples	Mj	Left Hand Portion	Right Hand Portion	Samples	Mj	Left Hand Portion	Right Hand Portion
1	0.15	0.075	0.575	16	0.38	0.19	0.69
2	0.34	0.17	0.67	17	0.3	0.15	0.65
3	0.28	0.14	0.64	18	0.24	0.12	0.62
4	0.33	0.165	0.665	19	0.74	0.37	0.87
5	0.2	0.1	0.6	20	0.47	0.235	0.735
6	0.45	0.225	0.725	21	0.43	0.215	0.715
7	0.45	0.225	0.725	22	0.36	0.18	0.68
8	0.32	0.16	0.66	23	0.3	0.15	0.65
9	0.48	0.24	0.74	24	0.44	0.22	0.72
10	0.66	0.33	0.83	25	0.19	0.095	0.595
11	0.3	0.15	0.65	26	0.24	0.12	0.62
12	0.45	0.225	0.725	27	0.25	0.125	0.625
13	0.34	0.17	0.67	28	0.64	0.32	0.82
14	0.47	0.235	0.735	29	0.37	0.185	0.685
15	0.24	0.12	0.62	30	0.46	0.23	0.73

Table 3: Results of applying fuzzy approach (0.70=ŧ)

Samples	Mj	Left Hand Portion	Right Hand Portion	Samples	Mj	Left Hand Portion	Right Hand Portion
1	0.15	0.105	0.405	16	0.38	0.266	0.566
2	0.34	0.238	0.538	17	0.3	0.21	0.51
3	0.28	0.196	0.496	18	0.24	0.168	0.468
4	0.33	0.231	0.531	19	0.74	0.518	0.818
5	0.2	0.14	0.44	20	0.47	0.329	0.629
6	0.45	0.315	0.615	21	0.43	0.301	0.601
7	0.45	0.315	0.615	22	0.36	0.252	0.552
8	0.32	0.224	0.524	23	0.3	0.21	0.51
9	0.48	0.336	0.636	24	0.44	0.308	0.608
10	0.66	0.462	0.762	25	0.19	0.133	0.433
11	0.3	0.21	0.51	26	0.24	0.168	0.468
12	0.45	0.315	0.615	27	0.25	0.175	0.475
13	0.34	0.238	0.538	28	0.64	0.448	0.748
14	0.47	0.329	0.629	29	0.37	0.259	0.559
15	0.24	0.168	0.468	30	0.46	0.322	0.622

Table 4: Results of applying fuzzy approach (0.90=ƚ)

Samples	Mj	Left Hand Portion	Right Hand Portion	Samples	Mj	Left Hand Portion	Right Hand Portion
1	0.15	0.135	0.235	16	0.38	0.342	0.442
2	0.34	0.306	0.406	17	0.3	0.27	0.37
3	0.28	0.252	0.352	18	0.24	0.216	0.316
4	0.33	0.297	0.397	19	0.74	0.666	0.766
5	0.2	0.18	0.28	20	0.47	0.423	0.523
6	0.45	0.405	0.505	21	0.43	0.387	0.487
7	0.45	0.405	0.505	22	0.36	0.324	0.424
8	0.32	0.288	0.388	23	0.3	0.27	0.37
9	0.48	0.432	0.532	24	0.44	0.396	0.496
10	0.66	0.594	0.694	25	0.19	0.171	0.271
11	0.3	0.27	0.37	26	0.24	0.216	0.316
12	0.45	0.405	0.505	27	0.25	0.225	0.325
13	0.34	0.306	0.406	28	0.64	0.576	0.676
14	0.47	0.423	0.523	29	0.37	0.333	0.433
15	0.24	0.216	0.316	30	0.46	0.414	0.514

Within the following part, we will provide the classic p control chart as well as the fuzzy p control chart for ϙ values of 0.50, 0.70, and 0.90.

Diagrammatic Representation of Control Charts

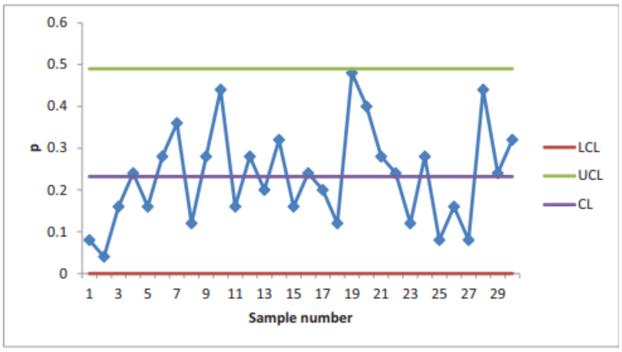

Figure 1: Shewhart p control chart

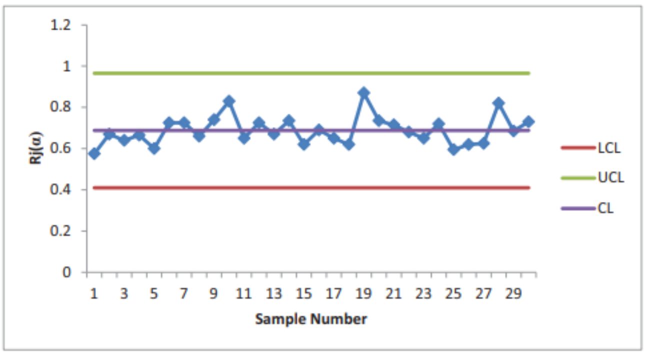

Figure 2: Fuzzy p Control Chart for 0.50 = ƚ (Right Hand Portion)

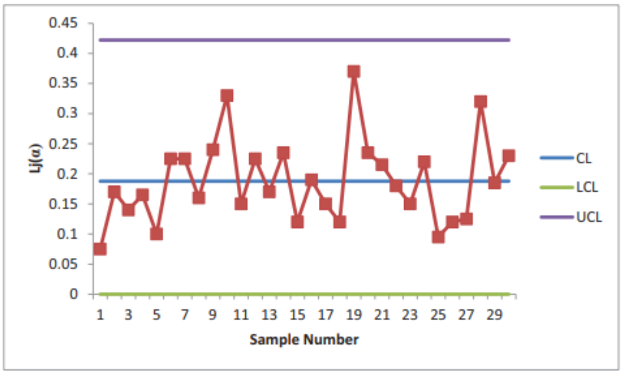

Figure 3: Fuzzy p Control Chart for 0.50 = ƚ (Left Hand Portion)

CONCLUSION

Statistical Process management, often known as SPC, is a tried-and-true technology that has an established track record of improving manufacturing quality via the methodical monitoring and management of production processes. Statistical process control (SPC) enables producers to discover and correct deviations in real time by utilizing statistical approaches such as control charts, process capacity analysis, and hypothesis testing. This helps to ensure that goods consistently meet or exceed the expectations of customers. Manufacturers have the potential to reap a number of important benefits by utilizing SPC. SPC, in the first place, aids in decreasing defects and non-conformities, which in turn helps to save expenses associated with rework, scrap, and warranties. Second, statistical process control makes it easier to optimize processes by locating areas where there is room for efficiency enhancements and waste reduction efficiencies. Thirdly, statistical process control improves decision-making by delivering actionable insights that are derived from data-driven analysis. This, in turn, generates informed modifications to processes and preventative actions. Furthermore, SPC helps to cultivate a culture of continuous improvement inside firms, which gives staff the authority to proactively identify and address quality concerns. By including frontline employees into the SPC process, businesses are able to capitalize on the knowledge and experience of these employees, which in turn drives genuine change and innovation. The successful adoption of SPC, on the other hand, necessitates a commitment and investment from management, in addition to efficient training and communication throughout the whole business. It is important for businesses to guarantee that their data gathering procedures are comprehensive and that their employees have received sufficient training in statistical methodologies and the interpretation of results. It may be concluded that statistical process control (SPC) provides a powerful foundation for achieving excellence in manufacturing and consistently providing goods of high quality. It is possible for manufacturers to achieve a competitive advantage in today's dynamic marketplace by adopting the concepts of statistical process control (SPC) and incorporating them into their operations. This will also help manufacturers cultivate a culture of quality and continuous improvement.

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