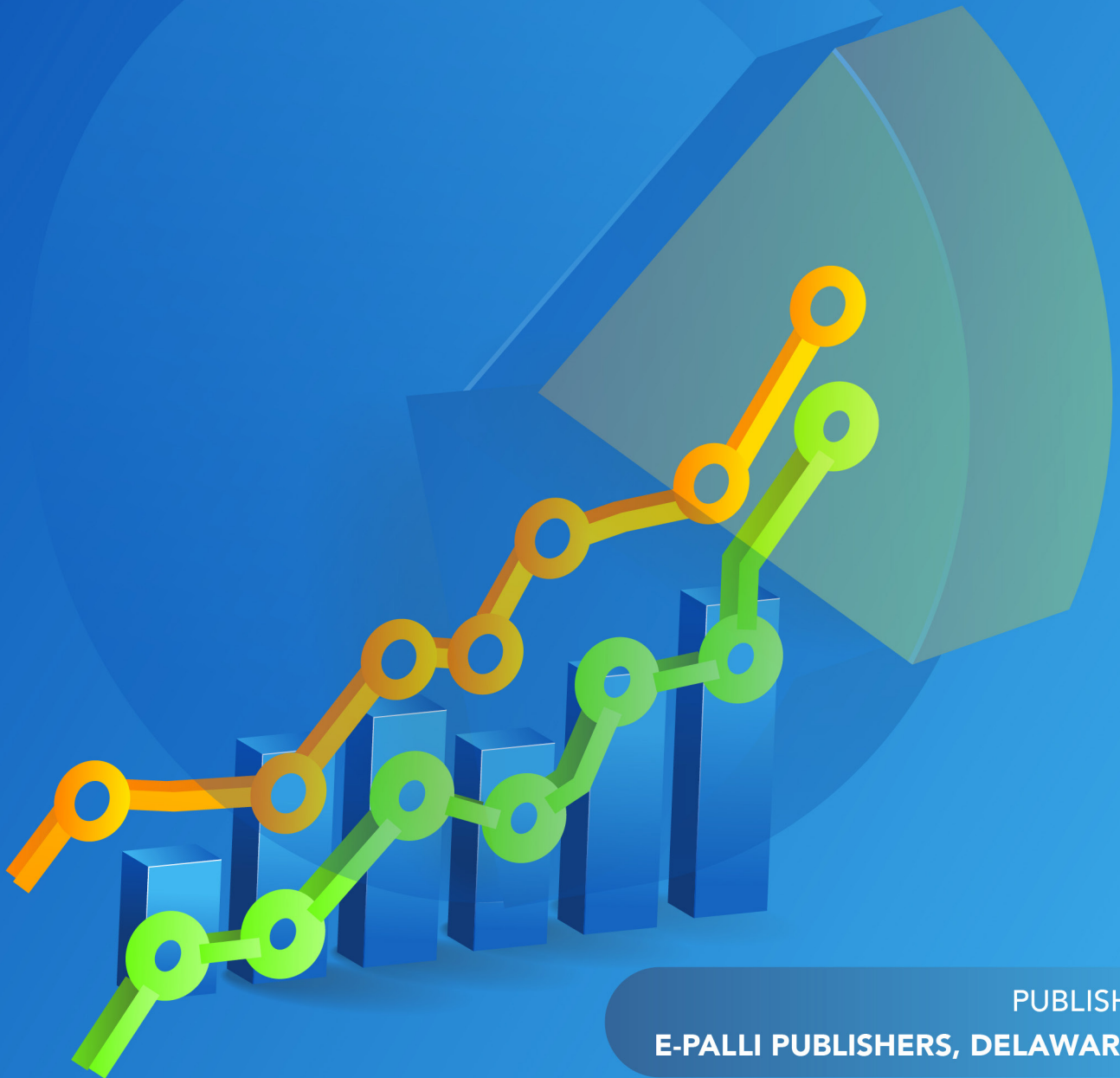




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Enhancing Business Performance Using Statistical Quality Control Techniques

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ABSTRACT

Quality control (QC) is central to ensuring that business processes produce goods and services that meet customer requirements and regulatory standards. Statistical methods underpin modern QC by enabling measurement, monitoring, and improvement of processes. This paper reviews the theoretical foundations of statistical quality control (SQC), describes key statistical tools such as control charts, process capability indices, and links them to business applications. It explores how statistics help identify variation (common-cause or special-cause), support decision-making, and drive continuous improvement (e.g., Six Sigma). Practical implications, challenges (data quality, assumptions, culture), and future directions (big data, multivariate control) are discussed. The aim is to provide business managers and researchers with a comprehensive overview of how statistics can contribute to effective quality control in business operations.

INTRODUCTION

In a competitive global business environment, maintaining product or service quality is essential for customer satisfaction, brand reputation, and profitability (Zacharias, 2022). Quality control (QC) involves the operational techniques and activities used to ensure that product characteristics meet established requirements. Statistics plays a pivotal role in QC by providing objective methods to measure process performance, identify variation, evaluate conformity, and guide improvement. This paper explores how statistical tools support QC in businesses. It reviews the major methods, discusses their applications and limitations, and outlines future directions.

LITERATURE REVIEW

The discipline of statistical quality control (SQC) emerged in the early twentieth century, primarily through the work of Walter A. Shewhart at Bell Labs, who introduced control charts to monitor process variation. Shewhart defined the central idea of distinguishing common-cause variation (inherent in the process) from special-cause variation (assignable factors) thus enabling process monitoring and control. Over time, SQC has been integrated into broader framework such as Six Sigma and total quality management (TQM). Among the approaches that stand out in SQC is the Six Sigma methodology, which when applied, can only allow a defect rate of not more than 3.4 per million opportunities. In such a process high-quality output is definitely assured. This approach emphasizes continuous improvement and data-driven decision-making (Connaughton, 2021). More recently, reviews have analysed the evolution of SQC tools and their research tradition (Nagar & Gahlot, 2022). In parallel, business-oriented research has explored how QC

practices impact reputation, market share and operational performance (Zacharias, 2022).

Statistical Quality Control techniques add value in multiple ways in business. Through real-time monitoring, businesses can detect drift or abnormal variation early, reducing waste and defects. Statistical tools enable managers to distinguish between common and special causes of variation, allowing targeted corrective actions. Sampling plans save costs compared to 100% inspection. Moreover, statistical summaries such as process capability or defect rates guide data-driven decision making. In framework such as Six Sigma, statistical measurement and analysis underpin the Define Measure Analyze Improve Control (DMAIC) process, ensuring systematic quality improvement (Connaughton, 2021). Strategically, effective QC enhances customer trust, reputation, and compelling competitiveness (Zacharias, 2022).

Theoretical Foundations: Variation, Capability, Control

All processes exhibit variation. The key theoretical insight from Shewhart is that if only common-cause variation is present, the process is “in statistical control”; if special-cause variation occurs, the process may produce unpredictable outcomes or defects. Control charts help visualize and distinguish these phenomena. Once a process is stable (in control), businesses can evaluate how well it meets specification limits using capability indices such as Process Potential Capability (C_p) or Process Centering Capability Index (C_{pk}), which rely on statistical measures of process mean and standard deviation. The objective is to keep the process within control limits so that only natural variation remains, facilitating predictable performance and enabling improvement initiatives. These indices are given by:

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$$C_p = (USL - LSL) / 6\sigma \quad \dots(1)$$

Where

USL is the upper specification limit

LSL is the lower specification limit

σ is the process standard deviation

It should be noted from equation (1), that a C_p value greater than 1.0 indicates the process has the potential to meet specifications. Though so, it doesn't consider if the process is actually centered. In other words it shows that the process could actually work if it is centered.

$$C_{pk} = \min\left(\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right) \quad \dots(2)$$

where

μ is the process mean

A C_{pk} value shows how well the process is centered between the upper and lower specification. From equation (2), if $C_{pk} > C_p$, then there is a high possibility that the process is not centered and may have a higher rate of defects. Further a C_{pk} value of 1.33 or more is considered good because it implies that less than 0.01% of the products will be scrapped.

Control charts are the hallmark of statistical process

control (SPC). For example, while \bar{X} and R (or s) charts are for variable data, p-charts, np-charts, and c-charts are for attribute data. Control chart rules help detect signals that may indicate special-cause also called assignable variation. Acceptance sampling, on the other hand, allows businesses to inspect samples rather than entire lots, reducing costs while maintaining confidence in product quality. Descriptive statistical tools such as histograms, Pareto charts, and scatter plots assist in diagnosing process issues, identifying major defect causes, and exploring relationships among variables. Inferential methods like regression analysis and Design of Experiments (DOE) support root cause analysis and optimization of process inputs.

RESULTS AND DISCUSSION

To illustrate the use of the control charts the real inbuilt dataset on piston rings in R has been used. This statistical process control charts were generated using R (R Core Team, 2024) with the qcc (Scrucca, 2004) and SixSigma (Panwar, 2023) packages. Figure 1 shows the \bar{X} -chart for the dataset while Figure 2 shows the corresponding R-chart.

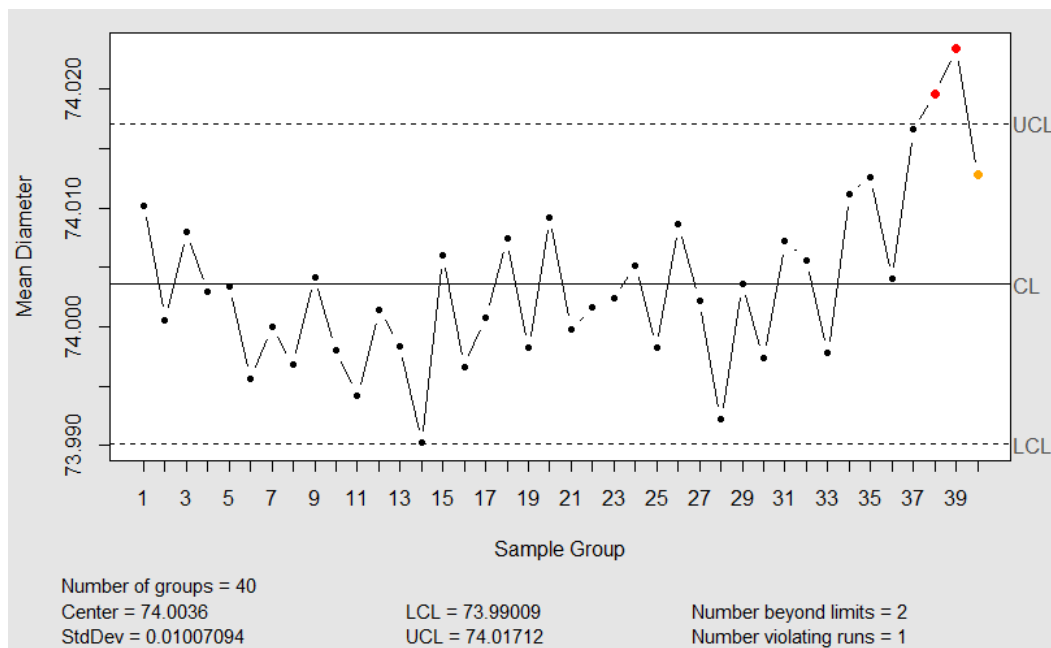


Figure 1: X-bar chart for piston ring diameters

In Figure 1 it is clear that 2 points are outside the upper control limit signifying that the process is out of control. In addition there was one (violating run) sequence of 2 points that violated the statistical rule. The process therefore needs to be stopped and action taken to correct. The R- chart is hereby presented in Figure 2.

According to Figure 2 the process is in control since all the points are within the lower and upper limits. Were it not for the \bar{X} -chart, it would have been concluded that the process is statistically under control. In general therefore the process is not in control.

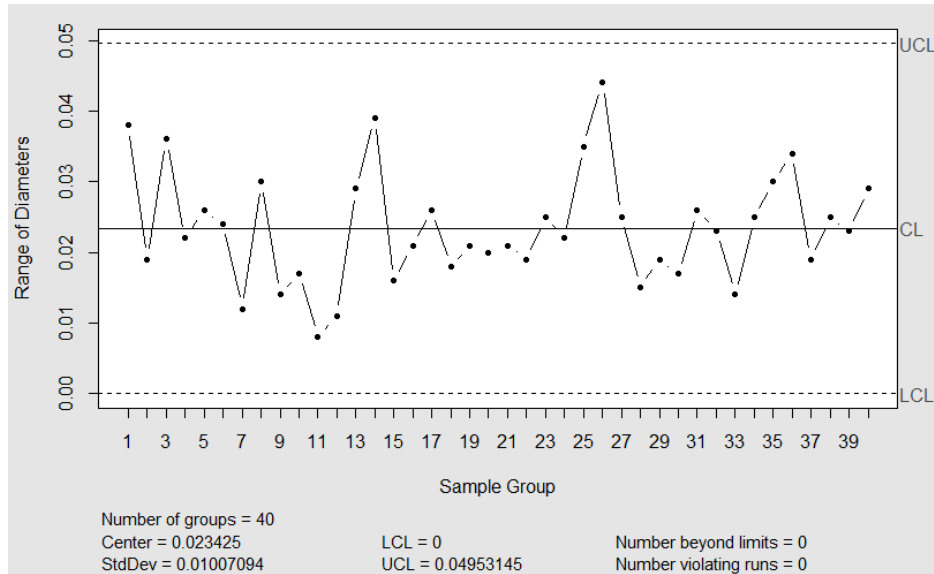


Figure 2: R chart for piston ring diameters

To facilitate the illustration of the analysis of the attributes, the dataset of orange juice from qcc was used. The dataset has the number of defectives or

nonconforming cans in each the sample of 50 drawn. It is particularly useful in monitoring the defect rate. The output is as given in Figure 3.

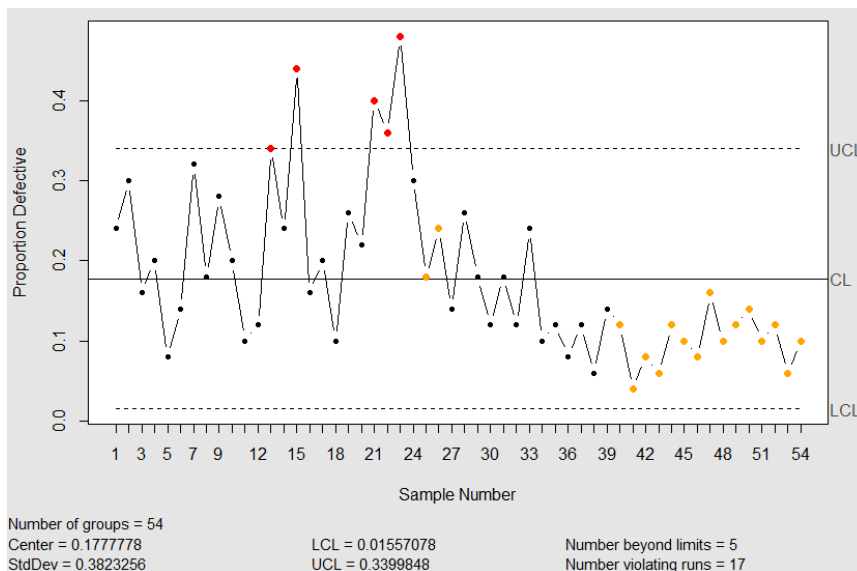


Figure 3: p- chart for defective orange juice bottles

In Figure 3 quite a number of points lie outside the limits. Specifically, 5 points are beyond the upper limits. Additionally, there are 17 violating runs portraying extreme case of pattern which is unacceptable even if all the points were within the limits. Clearly the chart in Figure 3 indicates an out of control process.

This study picks two commonly used indices (C_p and C_{pk}) as evaluated in Figure 4 which indicate the process capability of meeting the specification and the centralizing

factor. $C_p = 0.33 < 1$ implying the process does not meet the specification. The index that show the centeredness of the process is $C_{pk} = 0.212 < 1.33$. This value is far from 2 the index that corresponds to the high quality Six Sigma level of performance. It can therefore be concluded that the process is not capable of consistently meeting the specifications. With this outcome, action should be taken to reverse the situation. The process should be stopped and action taken to look for the cause of the problem.

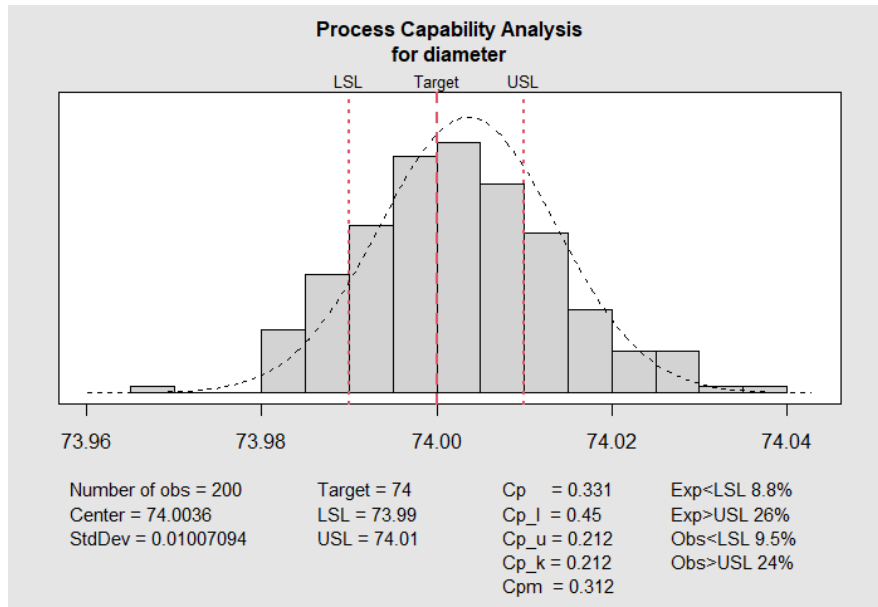


Figure 4: Process capability Analysis for diameter of the piston rings

Replacement of worn out parts or scraping of some parts equipment in use may be done to enhance the quality of the products.

This analysis of the dataset illustrates how statistical monitoring, detection of special-cause variation, corrective action, and capability analysis all combine to deliver business benefit

Challenges and Limitations

Although the statistical QC toolkit is powerful, there are several challenges. Data quality and measurement system error can mislead analysis. Many tools assume independent and normally distributed data; violations of these assumptions can invalidate conclusions. Cultural and organizational barriers can limit the effectiveness of QC if management fails to act on findings. The cost-benefit balance must also be considered, as overly complex statistical methods may not yield a return on investment. Finally, modern processes often involve multivariate and dynamic data that require more advanced statistical approaches beyond traditional charts.

Future Directions

The future of statistics in quality control lies in big data and real-time analytics. With the advent of sensors and Internet of Things (IoT), companies can collect massive amounts of data and apply machine learning to detect subtle patterns. Multivariate SPC methods will become essential as processes grow more complex. Moreover, statistical QC is expanding to service sectors like healthcare and finance, and integrating with sustainability metrics such as waste reduction and energy efficiency. These innovations will continue to redefine how businesses monitor and manage quality.

CONCLUSION

Statistics underlies effective quality control in business performance by providing tools to measure, monitor, analyze, and improve processes. From control charts to capability indices, from sampling plans to regression analysis, statistical methods give managers objective insight into variation and process performance. When appropriately applied and combined with organizational commitment, Statistical Quality Control can transform business performance from inspection to process management, yielding improved quality, reduced costs, higher customer satisfaction, and competitive advantage. Organisations should therefore invest in data quality, personnel training, and a culture of continuous improvement. Future advances in big data and multivariate analysis promise to broaden the scope and impact of statistical quality control even further.

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