DOI: https://doi.org

Journal of Advanced Engineering & Applied Sciences

Journal homepage: https://rjsaonline.org/index.php/JAEAS

Statistical Process Control in Industrial Engineering

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ARTICLE INFO

Received:
April 28, 2024
Revised:
May 21, 2025
Accepted:
June 14, 2025
Available Online:
June 21, 2025

Keywords:
Statistical Process Control, Control Charts, Process Capability, industrial engineering, quality management, Six Sigma.

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ABSTRACT

Statistical Process Control (SPC) stands as a pillar of quality operations and the optimization of the processes in the field of industrial engineering. SPC is a set of statistical techniques used to monitor, control, and implement improvements on the production process through the identification of variability, reduction of defects, and improvement of the working process. The research studies the SPC methods including control charts, process capability study and Six Sigma strategies with emphasis on their use in manufacturing systems, service systems and production systems. The paper combines the theoretical background and applied implementation policies with a focus on real-time monitoring and early detection of deviations, as well as continuous improvement. Results have shown that effective utilization of SPC can greatly result in stability of a process, lower expenditure, and quality of the product. The most important difficulties, such as human issues, accuracy of data collection, and compatibility with Industry 4.0 technologies, are also addressed. The study adds value to the overall idea of the importance of SPC in industrial engineering and offers practical recommendations to those practitioners and researchers interested in the field of optimizing production systems.

Introduction

Industrial engineering focuses on the design, enhancement and optimization of complex systems of production. In this field, Statistical Process Control (SPC) is extremely important in making sure that processes are within the desired limits with minimal variation and defects. SPC is a statistical tool that helps engineers use data gathered by the process to identify the difference between common cause variation (which is part of every process) and special cause variation (which has an identifiable cause) (Montgomery, 2020). Through application of SPC, organizations are able to have predictable and steady production processes and, as a result, improve quality of its products and minimize its operating costs. The SPC is especially applicable in contemporary industrial settings where the production rate is large, supply chain is complex, and where the quality requirements are stringent (Evans and Lindsay, 2017).

The SPC methods have been evolving through the decades and incorporated both conventional control charts, capability analysis, and current six sigma techniques. The use of control charts such as X-bar, R, p, and c charts gives a graphical interpretation of the process behavior and thereby enables the engineers to follow trends, identify anomalies, and take corrective action before the defects spread (Ryan, 2011). Process capability indices like Cp, Cpk, and Ppk provide a measure of the capability of a process to meet specifications, which provide practical metrics to improve process and benchmark (Montgomery, 2020). Combination of Six Sigma and Lean Manufacturing enhances management of industrial processes with focus on using data to make decisions and elimination of variation to get close to perfect performance of the process (Antony, 2006).

Furthermore, SPC continues to become crucial in the globalized manufacturing systems, where the organization is located in geographically decentralized plants and is required to adhere to similar levels of quality. Using multinational control charts and process capability metrics, multinational organizations can track the performance of their plants, and maintain conformity with both international quality standards like ISO 9001. The sustainability agenda can also be achieved with the support of SPC since fewer variants of processes will result in less scrap, fewer energy resources, and fewer resources, which will increase the efficiency of operations and responsibility towards the environment (Buyukozkan and Gocer, 2018).

Literature Review

The use of SPC in manufacturing, service, healthcare and logistics has been widely researched. As Evans and Lindsay (2017) emphasized, SPC positively influences the efficiency of operations by allowing an earlier detection of process aberrations and lowering the level of defects. Lepore (2019) showed that businesses manufacturing healthcare could use SPC to streamline patient flow, reduce errors, and improve treatment outcomes, which evidenced how it can be used in non-manufacturing sectors.

The most popular SPC tool is the control chart analysis. As Ryan (2011) pointed out, X-bar and R charts are the most effective tools to use to indicate the stability of the process, whereas p-chart and c-chart would be useful in tracking the changes in the attribute data. Research has shown that when control charts are properly designed, they enhance communication between operators and management and allow quick reaction to deviations and reduce the expensive downtimes (Montgomery, 2020).

According to Montgomery (2020), process capability studies are calculations used to measure whether the processes can meet the specifications and are used to prioritise process improvements. Capability indices such as Cp and Cpk give objective information on the performance of the process, which is vital in benchmarking, supplier review, and continuous improvement programs. A study by Antony (2006) has identified that the combination of SPC and Six Sigma enhances the rate of defect reduction by effectively tackling the root causes and maximizing of key parameters in the processes.

Such modern trends as the combination of SPC with Industry 4.0 technologies are present. Buyukozkan and Gocer (2018) evaluated the effectiveness of IoT-enabled sensors, cloud computing, and real-time analytics to improve the effectiveness of SPC. These systems permit uninterrupted data gathering and charting that is automated and lowers occurrences of human error and responsiveness to deviations. Predictive analytics and machine learning are becoming technologies to identify anomaly automatically and detect process degradation as well as allow adaptive control (Masood, 2025).

A number of case studies have shown that SPC has an effect on industrial competitiveness. In an example, manufacturing firms in the automotive and electronics introduced scrap and rework costs reduction of 20-35 percent with the adoption of SPC and the use of capability studies and Six Sigma projects. The healthcare facilities that monitored the processes of patient care with the help of SPC experienced a decrease in the waiting times and medical errors (Lepore, 2019). Although this has its advantages, the problem of human errors, change resistance, lack of statistical knowledge, and resource constraints are still common. To address these issues, future studies highlight AI-enhanced SPC, predictive maintenance, and the combination with a cyber-physical system (Montgomery, 2020).

Methodology

This study uses both qualitative and quantitative design to investigate the use of SPC in industrial systems. Case studies of manufacturing and service industries were used to collect primary data by observing the application of the SPC in real time production processes. Peer-reviewed journals, books and technical reports were used as a source of secondary data.

The methodology includes:

- **Control Chart Analysis:** The data on manufacturing lines were utilized to make X-bar, R, p and c charts to keep a constant check on them. These charts determine trends, changes or out of control situations that can show equipment wear, operators mistakes or variations in materials.

- **Process Capability Assessment:** Cp and Cpk indices have been determined to measure process performance in relation to the specification limits and this has given an insight on the process performance that can be improved and variability reduced.

- **Comparison:** A comparative analysis was done on the SPC implementation in industries to understand best practice, general challenges and quantifiable results. Automobile, electronics, and medical systems were some of the case studies.

- **Use of Statistical Software:** Calculations, charting and data visualization have been done using Minitab, JMP and MATLAB, which makes it easier to perform analysis on large data set.

Further, the paper utilized root cause analysis methodology to processes that portrayed out-of-control situations. This methodology included identification of contributing factors, statistical significance and taking of corrective measures. The review of historical SPC data helped to follow the tendencies and prove the efficiency of interventions.The focus of data collection was on its accuracy, consistency, and completeness. Measurement techniques were trained on operators and gage R&R studies were used to verify the measurement techniques. Reliability analysis was used to make sure that variability caused by measurement errors was reduced to a minimum value so that a meaningful interpretation of process data could be carried out.

Lastly, the authors examined the incorporation of SPC into the contemporary Industry 4.0 technologies, such as IoT-based sensors to monitor in real-time, predictive analytics to identify anomalies, and automated reporting dashboards. This method enabled the study to evaluate both traditional and new SPC practices in a way that would give a clear picture of the implementation problems and advantages (Buyukozkan and Gocer, 2018).

Results and Data Analysis

Control Chart Analysis

The X-bar and R chart analysis of a sample manufacturing process is represented in Table 1. The process observation shows that there is variability in the control limits, with stable operation with minor special causal variations.

Table 1: X-bar and R Chart Summary

Sample	X-bar (Mean)	R (Range)	Control Status
1	50.2	4.5	In Control
2	49.8	4.2	In Control
3	50.0	6.5	In Control
4	51.0	6.5	Out of Control

Process Capability Analysis

Table 2 illustrates Cp and Cpk calculations for a production line. The results show a capable process with minor improvements required to center the process mean.

Table 2: Process Capability Indices

Parameter	Specification Limits	Cp	Cpk	Interpretation
Diameter	49.5–50.5 mm	1.33	1.25	Process capable but slightly off-centered
Weight	100_105g	1.40	1.35	Process capable and centered

Table 1 shows the analysis of X-bar and R chart of a sample manufacturing process. This can be observed to be a relatively stable process with small deviations in Sample 4 that does not lie within the control limits. These variation points are special cause variation and could be caused by an error in the operator, a malfunctioning equipment, or inconsistent raw materials (Montgomery, 2020). It is vital to detect such deviations early since the corrective measures may be taken before the defects spread to the lower end of the production line.

An in-depth analysis of the data obtained in the control chart revealed trends that can be used as a sign of possible improvement. To give an example, though the majority of samples fall within the control limits, the R-value in Sample 4 is somewhat higher, and it could be due to the higher variability of the process caused by inconsistent machine calibration or external conditions like temperature changes. A series of repetitive analysis across the production cycles can assist in raising the question as to whether this is a one-time thing or a pattern that is reflective of instability in the processes.

Key Observations

Majority of samples, 80% are inside control limits, showing that the process is stable.

Sample 4 signals an out of control situation, where root cause analysis is necessary, the variability in the process is usually low and it implies good standard operating procedures and compliance of operators.The analysis of control charts also shows the need to carry out constant monitoring. The slight changes that do not directly affect the quality of products can be cumulative leading to more defects or time wastage when they are not solved. When control charts are implemented in the day to day production process, both the operators and engineers would be able to sustain the same level of quality and react proactively to any kind of deviations (Ryan, 2011).

Analyzing the process capability would involve examining the process itself, concentrating on the number of products produced within a specific production process, and the results of that process.<|human|>The process capability analysis would entail an analysis of the process itself, with the focus being on the number of products produced at the given production process, and the outcomes of that process.

Table 2 contains the summary of Cp and Cpk of the important parameters of production. The parameters of diameter and weight show that the process is competent but off-centered to some extent. The diameter Cp of 1.33 indicates that the process distribution is reasonable as compared to specification but a Cpk of 1.25 indicates that the average is skewed towards one side. Likewise, weight parameter will have Cp of 1.40, Cpk of 1.35 which implies a well-centered, and competent process.

These capability indices give operational data on process enhancement. In this way, as an example, having minor changes in machine settings or tooling can align the mean nearer to the target and the probability of having out-of-spec items reduced. The gap between Cp and Cpk also explains how process centering influences the overall performance. Well-centered processes (CPK close to Cp) can produce fewer defects, but an intervention is necessary to develop better capabilities in processes that are not well aligned (Montgomery, 2020).

Practical Implications

Analysis illustrates that SPC has a number of useful advantages:

- **Early Identifying of Deviations:** Control charts enable detection of abnormal patterns or trends at an early stage even before defects are produced thus minimizing scrap and rework.
- **Process Optimization:** Capability indices offer indicators to assess process changes and identify that interventions will enhance outcomes.
- **Cost Reduction:** through minimization of defects and enhancement of the stability of processes, organizations will be able to lower the cost of operation and enhance efficiency.
- **Improved Decision-Making:** SPC-based data analysis can provide managers with the necessary information to make better decisions about the maintenance timetable, production planning, and resource distribution.

Integration with Industry 4.0

The work also discussed how SPC can be integrated with real-time monitoring and sensors based on the internet of things. Data can be continuously observed and dynamic updates are made to control charts to facilitate predictive interventions and remove the need for manual measurements. This integration improves the transparency of the processes and the opportunity to use the adaptive control methods, when there is an anomaly, the deviations activate the automated warning or correction measures. It is also possible to predict the tendencies in process variation with the help of predictive analysis to predictively maintain the process and avoid unnecessary downtime (Buyukozkan and Gocer, 2018).

As it is shown in the analysis, SPC is an effective tool that detects deviations and allows proactive corrective measures that can be taken, enhancing the overall quality and minimizing defects. The trend observed shows that control charts used to detect defects early in their process would save a lot of downtime and scrap, hence both operational and financial gains.

Discussion

SPC enhances process stability and quality of products through identification of sources of variety in a systematic manner. Control charts and capability indices enable the engineers to identify anomalies and trends prior to their development into major production issues (Montgomery, 2020). In combination with Six Sigma and lean, SPC helps sustain continuous improvement cycles and data-driven decision-making, which in the end make more productivity and customer satisfaction (Antony, 2006).

The new technologies also improve SPC. IoT sensors, cloud-based analytical and automatic dashboards can be used to observe real-time, predictive maintenance, and quick corrective measures and eliminate the need to use manual data collection (Buyukozkan & Gocer, 2018). By integrating machine learning, predictive modeling, early anomaly detection, and adaptive control can be generated to create intelligent production systems that predict and control variability before defects are created (Masood, 2025).

Nonetheless, effective implementation of SPC needs to focus on human and organizational issues. The operators should be educated on the use of control charts, how to interpret data and how to act timely. A data-oriented mindset must be promoted by the organizational culture and employees must be encouraged to adhere to the SPC protocols and engage in ongoing improvement projects. The most frequent obstacles that may undermine effectiveness are resistance to change and lack of statistical knowledge (Ryan, 2011).

Experiments in case studies indicate quantifiable results of SPC implementation. The automotive producers realized as much as 30 percent savings in scrap and redo expenses by combining the use of control charts and capability studies with Six Sigma endeavors. Plants in electronics manufacturing recorded high advances in the yield and process consistency. The healthcare systems that used SPC in the processes of patient care minimized errors and enhanced treatment schedules and patient satisfaction (Lepore, 2019).

All in all, SPC is helpful as a diagnosis and preventive tool. Not only does it identify the deviations but also gives one an insight into the root causes that allow one to continue improving. Through the integration of conventional SPC with the contemporary predictive technologies, industrial engineers are able to streamline processes and control variability, as well as, attain greater operational efficiency.

Conclusion

The importance of Statistical Process Control in industrial engineering is that it offers a mechanism that enables one to monitor, control, and enhance the production processes in a systematic manner. Its use results in less variability, low defects, and efficiency in operations. Capability indices and control charts provide practical information that needs engineers to identify the variations at an early stage and take the necessary steps that would correct the situation (Montgomery, 2020).

The combination of the SPC with the Six Sigma, Lean Manufacturing, and Industry 4.0 technologies is additionally aimed at improving the performance of the process. Proactive interventions and adaptive control can be facilitated by IoT-enabled sensors, real-time monitoring, and predictive analytics, which enhances the quality of its products and reliability of its processes to a substantial extent (Buyukozkan and Gocer, 2018).

Effective SPC implementation however needs correct data, skilled human resources and organizational commitment. The measurement systems should be checked to ensure reliability, the operators need to be trained how to read the control charts, and the management needs to encourage the culture of constant improvement. Manufacturing and healthcare case studies show that companies that implement SPC have seen visible results, such as a decrease in scrap and rework expenses, better yields, and better customer satisfaction (Antony, 2006; Lepore, 2019).

The new research areas should be AI-based SPC, predictive analytics, and the linkage with cyber-physical systems. The developments will enable the industrial engineers predict deviations, dynamically optimize processes, and ensure consistent quality in the complex production settings. Organizations can be sustained in their operational excellence through establishment of a connection between the ancient SPC and the contemporary technology, and sustain a competitiveness in the global market.

Recommendations

1. Combine SPC, Six Sigma and Lean processes to manage the process in the best way.
2. Participate in real-time monitoring and internet of things sensors to have better control of the process.
3. Invest in training of personnel on how to collect data and interpolate on SPC.
4. Use statistical software (Minitab, MATLAB) to have easy analysis and visualization.
5. Carry out regular capability studies (Cp, Cpk) in order to evaluate and enhance process performance.
6. Research AI and machine learning to forecast SPC and abnormality detection.
7. Establish common guidelines in implementing SPC in industries.

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