



Original Article

A Survey of Statistical Process Control and Its Applications in Manufacturing Quality Assurance

Muzaffer Hussain Syed¹, Uday Kumar Ragireddy², Prasanth Varma Addepalli³, Sridhar Reddy Bandaru⁴, Dhuli Shyam⁵, Prabu Manoharan⁶

¹Sr Software Developer, Visual Technologies, Plano, TX.

²Sr Technical Program Manager, Vdrive IT Solutions, Inc, Richardson, Texas.

³Data Engineer II, Cox Automotive Corp Svcs LLC, Atlanta, Georgia.

⁴Program Management, IT, Microsoft, Senior ACE Engineer, Redmond, WA.

⁵Business Application, IT, Nagase Holdings America Corp, Manager, Application & Software Development, NYC, NY.

⁶Information Technology, Bourns Inc, HRIS Manager, California, USA.

Abstract - The high-quality products are one of the challenges that industries must guarantee, which rapidly develop in terms of global manufacturing. The quality of the finished product and its degree of functioning, and the customer satisfaction may all be altered substantially by the changes in the manufacturing cycle. Statistical Process control (SPC) is a method which incorporates the application of statistical methods in inspecting, regulating and improving industrial processes. The paper provides a thorough summary of SPC and how it has been used in the manufacturing quality assurance, which is essential in ensuring that variability in processes is eliminated, to enhance the consistency of the products and this is to reduce waste. The control charts, Pareto analysis, cause-and-effect, and process capability assessment are the most commonly used SPC tools that are described and accompanied with the description of how this tool is used in practice. The use of SPC in the practical implementation of manufacturing industry is also discussed in the paper which illustrates its practical use in making sure that processes are doing a good job and provide quality compliance. Moreover, the study illustrating the applicability of SPC in a manufacturing environment and its ability to lead to measurable increase in process capabilities and reduction of defects are also present. The paper identifies the importance of SPC as one of the keystones in the quality management systems in the contemporary production.

Keywords - Statistical Process Control, Analysis Manufacturing Systems, Variation Reduction, Industrial Quality Management, Continuous Improvement.

1. Introduction

The manufacturing has taken a very high level and interrelated form, and it embraces all sorts of production processes, human skills, and modern equipment to meet the constantly increasing demands of the global economy. The scope of manufacturing activity has been expanded because of the development of industries and need to compete in the world market, which resulted in the development of complicated supply chains, decentralized manufacturing locations, and higher standards of performance. They have also been further aggravated by globalization and the shift of the production base and the reliance on outsourced manufacturing compelling organisations to persist with high quality requirements despite the geographical distribution of operations [1]. These changes demonstrate that it is important to have powerful mechanisms that can lead to consistency, reliability and competitiveness in the new manufacturing environment.

Quality management that is a core pillar of knowledge-based economy and digital economy is the key in terms of meeting these demands [2]. This is due to the complexity of the quality assurance mechanisms that are needed by the quality of smart, technology-enhanced products and their reliability as they cover all the manufacturing lifecycle stages. Such systems are supposed to be integrated with organizational information technology in order to enable real-time decisions and transparency of the processes as well as continuous enhancement. However, the development and maintenance of software solutions that can be used to perform such quality-related features remains a continuous issue as the quantity, sophistication, and pace of production information are ever-increasing [3]. This dynamic environment is the one that demands methodologies that can transform raw process information into intelligent information.

The Statistical Process Control (SPC) approach is one such essential methodology. Because SPC is a scientific method that is based on the scientific principles of statistics, it allows manufacturers to track and manage variability of processes to maintain constant operations that lead to the delivery of compliant products [4]. The evidence-based approach to decision-making leads to the application of data instead of subjective evaluations, and improves consistency in the outcomes of processes through the assistance of SPC in place [5]. Achieving control charts, continuous improvement strategies and experimental designs are the fundamental elements that render SPC effective in providing systematic avenues of identifying deviations, assessing process capability, in addition to simplifying the performance. The peak of its application in industries is an indication of its effectiveness in enhancing the quality and competitiveness of the organization.

The combination of the SPC and IT-based quality assurance systems is increasingly becoming urgent due to the further introduction of automation, digital platforms, and smart technologies in the manufacturing systems [6]. The modern use of SPC is founded upon the multi-faceted data collection systems, real-time monitoring structure, and automatic analytics to realize a more exact and responsive control over the variability in the processes [7]. These advancements extend the horizons of conventional SPC since it allows tracking process conditions, in great detail, continuously, and distributed production phases [8]. Integrated as part of digital quality management systems, SPC helps pursue the global quality standards, reduce waste, and reinforce continuous improvement efforts.

1.1. Structure of the Paper

The following is the structure of the paper: the foundations of statistical process control are covered in Section II. SPC applications in manufacturing industries, section III. The SPC implementation case study is described in section IV. Section V brings the overall conclusion of SPC in Manufacturing Quality Assurance.

2. Fundamentals of Statistical Process Control

The use of statistical approaches to monitor and manage a process to make sure it runs as effectively as possible to generate a conforming product is known as SPC. In order to produce as much conforming product as possible with the least amount of waste, a process runs dependably under SPC. Important SPC tools include design trials, control charts, and continuous improvement [9][10]. In general, there are three methods for using SPC tools.

2.1. SPC software

Its advantages include ease of use, comprehension, and data storage and retrieval. Its drawbacks include operator delays when inputting data into the system, operator mistakes while entering data, and the inability to create pie or bar charts [11].

2.2. SPC in Excel sheet

It has a rudimentary visual facility and is straightforward and easy to comprehend. Its drawbacks include the incapacity to accommodate many users, operator mistakes in data entry, and a function that alerts employees when an out-of-specification value occurs.

2.3. SPC with manual application

It entails utilizing graph paper to manually draw data on control charts. When these technologies are used for the first time, their benefits are straightforward and excellent. However, when used for the first time in industrial sectors with minimal quality defect incidences, these are vulnerable to significant constraints.

2.3.1. SPC implementations

As seen in Figure 1, when employing SPC, it's necessary to analyse and discover vital product features that customers appreciate or relevant process variances. The crucial actions for putting SPC into practice are:

- Identify defined processes
- Identify measurable attributes of the process
- Characterize natural variation of attributes
- Track process variation
- If the process is in control, continue to track
- If the process is not in control
 - Identify assignable cause
 - Remove assignable cause
 - Return to 'Track process variation'

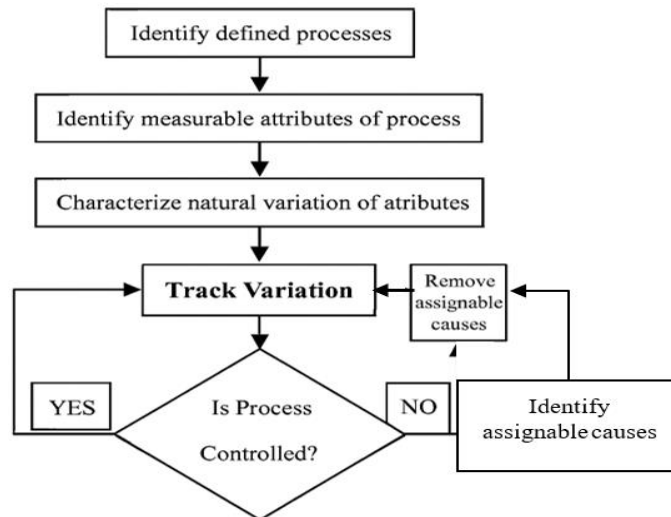


Figure 1. Steps in SPC implementation

In order to plan for quality control operations, it is necessary to apply the Pareto effect to determine the essential few processes that regulate manufacturing [12].

2.3.2. Statistical Process Control tools

In practice, reporting on SPC is usually manufacturing on a few processes in the manufacturing industry. Because of this, SPC has been in charge of formal testing, maintenance, inspections, and personal development. [13]. 7 QC techniques are straightforward statistical techniques for tackling issues. Quality preceptors like Deming and Juran created these tools. Figure 2 illustrates the seven high-quality instruments that may be used to enhance procedures.

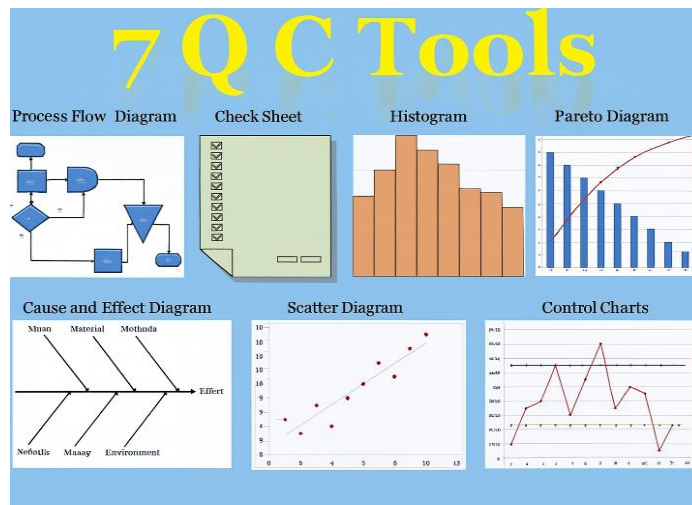


Figure 2. The seven SPC tools

- Pareto Chart: The heights of the bars on the Pareto Chart, which bears the name of the Italian economist Pareto, show the importance or frequency of certain problems. The bars are positioned from left to right in decreasing height order [14]. This implies that the tall bars on the left reflect categories that are comparably more significant than those on the right.
- Cause-and-Effect Sheet: It aids in structuring the brainstorming process and arranges and illustrates the relationships between the many aspects of the impact being studied.
- Scatter Diagram: It is sometimes referred to as a scatter plot or an X-Y graph. A scatter diagram is one way for exploring the relationships between two variables. The horizontal axis illustrates the independent variable, whereas the vertical axis represents the dependent variable.
- Flow Chart: This style of diagram illustrates an algorithm, workflow, or process by linking the stages with arrows and displaying them as different types of boxes.

- Histogram: A histogram is a fundamental tool of high quality. It is employed to visually represent and summarize a process data set's distribution and variance [15]. The frequency of each distinct value in a collection of data is shown in a frequency distribution. A histogram's primary purpose is to indicate the kind of data being collected.
- Check sheets: These are only data collection charts. Check sheets that are neatly and plainly created help collect relevant and correct data and make it simple to read and utilize.
- Control Charts: These are graphical tools that SPC and facilitate the identification of out-of-control locations and processes without the need for complex statistical testing.

3. Applications of Spc in Manufacturing Industries

Statistical Process Control (SPC) helps manufacturing companies improve product quality, process consistency, and variability. Numerous industrial industries make substantial use of its tools, such as variation monitoring, process capacity analysis, and control charts. The following section brings to the fore five key areas in which SPC can contribute towards a better-quality manufacturing [16].

- Manufacturing: In the industrial sector, SPC is widely used to visualise and control the process with the purpose of boosting product quality [17].
- Healthcare: SPC is widely used in the healthcare industry to track patient development and health [18].
- Service Industry: SPC is being utilised more and more in the service sector to keep an eye on and enhance the calibre of services offered to clients. Call centers, for instance, can utilize SPC to monitor how many calls their operators handle, how long it takes to answer client questions, etc.
- Financial Industry: Financial data, including stock prices, interest rates, and currency rates, are monitored and analyzed by SPC. It assists in finding patterns and trends in the data so that decisions may be made with knowledge.
- Software Development: SPC may be used in software development to keep an eye on and manage software product quality. It may be used to keep an eye on performance indicators, track errors, and make sure software development processes are under control [19].
- Supply Chain Management: SPC may be used in supply chain management to track and enhance process and product quality. It may be used to keep tabs on stock levels, keep an eye on suppliers' performance, and make sure delivery deadlines are fulfilled.
- Environmental Monitoring: Environmental data, including weather patterns, climate change, and the quality of the air and water, may be tracked and analyzed using SPC. It assists in finding patterns and trends in the data that may be utilized to make well-informed choices on environmental laws and regulations.

4. Case Study of Spc Implementation

In implementing 20 samples, each including 30 body length measurements, were gathered using SPC techniques in order to create x and R control charts. The charts shown in Figure 3 were created using Minitab®. This graphic shows that the x chart has an out-of-control point [20] [21].

As a result, an alert was set off to establish that it was an uncontrollable process. Following a brainstorming and CEA analysis session, the quality management team discovered one potential assignable reason that led to the production process for capsules is becoming unmanageable [22].

This was the abrupt shift in the facility's atmosphere's relative humidity. After an enhanced monitoring policy and room humidity management were adopted, The x and R control charts were created using a fresh batch of samples. There were no out-of-control points on the current charts.

As seen in Figure 4, the CUSUM control chart was made using the last batch of samples once more. This graphic shows that the third sample has an out-of-control point. As a result, the cutting mechanism's repeated screw adjustment was given more attention, while other possible causes were investigated [23].

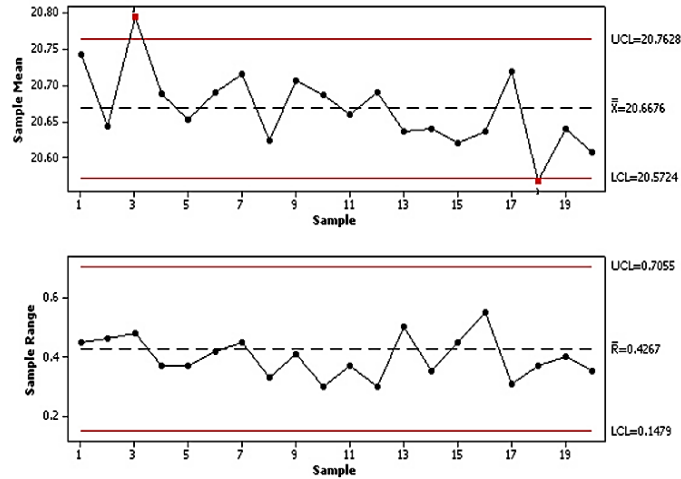


Figure 3. X And R Control Charts at the Beginning of the Implementation of SPC

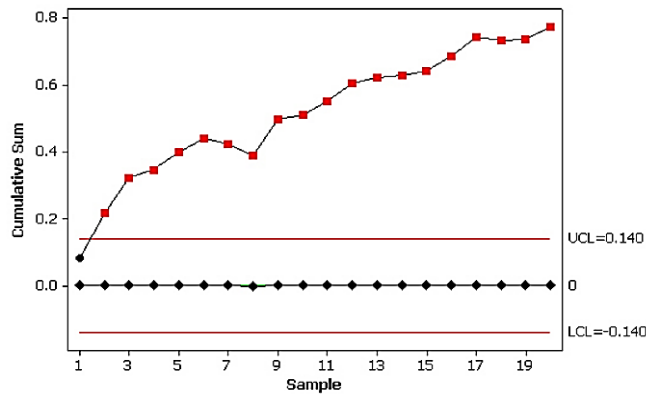


Figure 4. CUSUM Control Chart With Out-Of-Control Point

The same process was performed in Phase when there were no alarms, and the cutting process was changed to remove the requirement for screw adjustment. Furthermore, additional CUSUM control charts were created every week, but there were no alarms. A 17-week evaluation of the process capability index (PCI) was conducted.

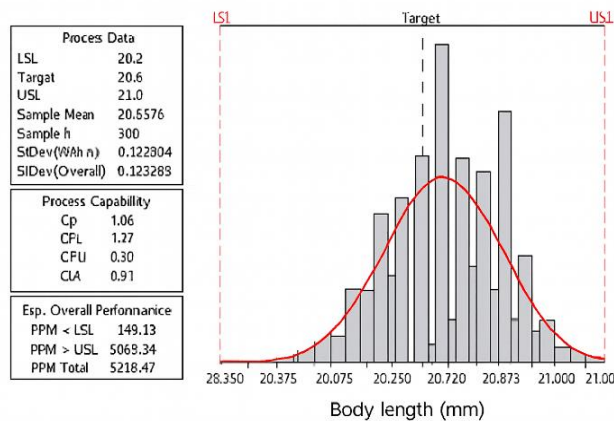


Figure 5. Process Capability Output At The Start Of Implementation Of SPC

Figures 5 and 6 depict the process capability output at the beginning of implementation and 17 weeks later. Figure 5 shows that the process mean (sample mean = 20.5576 mm) is initially off-target. This translates to an anticipated 5218 capsules per million that have body lengths that are not within standards.

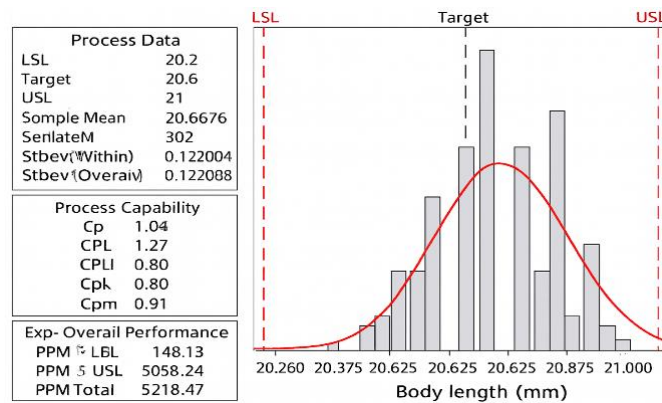


Figure 6. Process Capability Output After 17 Weeks Of Implementation Of The Three-Phase Scheme

Figure 6 demonstrates that, with a CPM value of 0.91, the process mean is nearer the goal (sample mean = 20.6 mm). Therefore, using the SPC techniques utilized in this study can result in an anticipated 20% decrease in the quantity of capsules that don't fit the specifications due to improper body length.

5. Literature Review

This section summarizes the entire research 'Statistical Process Control and Its Applications in Manufacturing Quality Assurance' in detail and also presents a brief version of the content in Table I.

Razmochaeva, Semenov and Bezrukov (2019) The major components of statistical control of quality management methods for goods and continuing firm operations are explained. A comparative analysis of the statistical management software currently in use is conducted based on the chosen comparison criteria. Systems' benefits and drawbacks are identified, and a response to the query of each system's suitability for the process automation issue is developed. The primary strategies for updating the current systems and creating new ones for statistical process management are assigned [24].

Saif (2019). Subsequent studies revealed that combining these two strategies produces greater results than employing each one alone. The advancements in integrating these two methods thus far are the initial focus of this study. After that, a suggested plan to combine SPC and APC to complete a few tasks is shown. There is a focus on new research avenues for combining these methods [25].

Godina and Matias (2018) Special cause events are identified and tracked using statistical methods. The SPC is a technique for preventing errors rather than identifying them. This paper's case study involves a Portuguese small- and medium-sized automotive firm (SME) that implements SPC. The test of normality applied in the SPC chart of the plant is the Kolmogorov-Smirnov test (K-S). The control chart has been assessed, and it reveals that the process is focused and is well within the norms of quality compliance. Additionally, the K-S test verifies the normal distribution of the acquired data. The Shapiro-Wilk test is a more trustworthy measure of normality than the K-S test, even if the findings may differ [26].

Cooke and Howe (2018) The well-known technique is statistical process control (SPC), which uses statistical analysis to track behaviour and regain control over process parameters. This method can be applied to investigate the time when power-quality (PQ) attributes are out of normal range, such as harmonics, imbalance, and flicker. However, the frequent deviation of these PQ characteristics may change depending on the day of the week, the time of day, and even the season. Instead of having a single restriction, a dynamic set of constraints would be selected to reflect unknown anomalies, resulting in a tighter set of continuous control during these times. This research discusses approaches for setting dynamic statistical process control limits with PQ data [27].

Crowell et al. (2018) A set of reference tools that support the parsing, display, and analysis of build-time sensor data in an intelligible and easily interchangeable file format is the result of this project. Jupyter Notebooks, a markup format that combines Python source code, output, and documentation, is the foundation of the suite. The EOS M 290 L-PBF printer's sensor data is the major emphasis of the product's interface, although its functionality is versatile and adaptable to varied applications. Members of CCAM's consortium use the final product for various devices and sensor kinds, and it may be customised to support the digital thread in a variety of investigations. [28].

Forbes et al. (2017) The project's main goal is to provide a non-destructive post-production verification method that helps users assess a part's quality by rendering 3D models of the real construction using photographic data. By 1) gathering and cleaning image data from actual builds, 2) efficiently storing data, and 3) producing visualisations of the images, the visualisation process described here automates some labour-intensive tasks and ultimately assists users in determining how print

parameters affect a build's quality. The ability to assess a final printed object's quality without damaging it for quality assurance inspection is an important result of this study [29]

Table 1. Summary Of Statistical Process Control And Its Applications In Manufacturing Quality Assurance

Source	Research Focus	Key Insights	Challenges	Limitations
Razmochaeva, Semenov & Bezrukov (2019)	Statistical control in quality management and comparison of statistical management software	Identified benefits and drawbacks of current statistical management systems; developed criteria-based comparative analysis; proposed strategies for upgrading and developing new systems for statistical process management	Selecting appropriate criteria for system comparison; integrating automation effectively into business processes	Existing systems may not fully support automation needs; improvements proposed but not tested empirically
Saif (2019)	Integrating Statistical Process Control (SPC) with Automated Process Control (APC)	Demonstrated that combining SPC and APC yields better results than using each individually; reviewed historical development; proposed an integration scheme and future research directions	Achieving effective integration of two different control methodologies; lack of unified frameworks	Proposed scheme not experimentally validated; relies heavily on prior theoretical work
Godina & Matias (2018)	Use of SPC for monitoring special-cause variations in an automotive SME	SPC analysis showed the process is centered and meets compliance; Kolmogorov-Smirnov test confirmed normal distribution; highlighted potential differences if Shapiro–Wilk test were used	Choice of statistical tests affects interpretation; balancing practicality vs. accuracy in real SME environments	Case study limited to a single SME; results may not generalize; normality tests may yield conflicting outcomes
Cooke & Howe (2018)	Dynamic SPC limits for power quality (PQ) data	Developed methods to create dynamic control limits to reflect time-dependent variation in PQ parameters; argued dynamic limits outperform static ones for abnormality detection	Accounting for temporal variation in PQ parameters; creating models robust across varying time scales	May require large, high-resolution datasets; dynamic limits can be complex to calibrate
Crowell et al. (2018)	Tools for analyzing, visualizing, and processing build-time sensor data in additive manufacturing	Developed a modular, Jupyter-based tool suite for analyzing L-PBF machine sensor data; adaptable to various machines and sensors; supports digital thread implementation	Ensuring compatibility across diverse machines and sensor types; maintaining modularity while supporting advanced analytics	Tool performance dependent on sensor data quality; not all sensor types tested
Forbes et al. (2017)	Non-destructive 3D visualization for quality verification in additive manufacturing	Automated data cleaning, storage, and visualization of build images; enabled quality assessment without destroying the printed object; improved understanding of how printing parameters affect final quality	Handling large image datasets efficiently; automating complex visualization tasks	Visual models may not capture hidden internal defects; accuracy depends on image resolution and consistency

5.1. Research Gap

In spite of the fact that the previous research has discussed the SPC issue in a variety of aspects such as comparing the statistical management software, incorporating SPC with Advanced Process Control (APC), using SPC in SMEs, creating dynamic control limits, and the non-destructive verification of quality, the gaps are still present. The available research is rather biased on specific case studies, or tool-based applications, or even domain-specific applications, but does not present an integrated framework that can encompass dynamic SPC strategies, use of sophisticated data analytics, and real-time monitoring in a wide variety of manufacturing settings. In addition, there is a preference in most research to focus on the classic statistical tests and fixed limits, whereas there has been a little acceptance of adaptive, data-driven, and automated SPC systems that can process high volumes of sensor data and dynamically adapt to process conditions. Such fragmentation underscores the necessity to have an all-inclusive, scalable, and smart SPC-based quality assurance model that would help bridge the traditional statistical techniques with the latest digital manufacturing technologies.

6. Conclusion and Futur Work

The Statistical Process Control (SPC) has demonstrated to be one of the most essential methods for boosting quality control in the production process. SPC allows enterprises to maintain a constant quality of their goods, eliminate wastes and boost operational efficiency by recognising and limiting variability of the processes. The article covers the principles of SPC, Pareto analysis, cause-and-effect diagrams, control charts, process capacity assessment, and their real-world applications. The study illustrates that process capability, and defect reduction can be measured and conclude that SPC is an effective tool in the actual production setting. On the whole, SPC is the general approach to the contemporary quality management systems that make it possible to make informed decisions and improve continuously and follow the international standards of quality in the manufacturing industries. Future study can concentrate integrating SPC to the emerging Industry 4.0 technologies (AI-based predictive analytics, automated quality control systems and IoT-based real-time monitoring) to the extent of the upcoming study. This kind of integration would improve the precision and speed of identifying the process variations, maximize the production efficiency, and boost the application of SPC in different industrial and service industries. Also, the investigation of adaptive SPC models of dynamical processes and high-mix production facilities may further enhance the reliability of the processes and decrease defects in the contemporary manufacturing.

References

- [1] A. Hussein and K. Cheng, "Development of the supply chain oriented quality assurance system for aerospace manufacturing SMEs and its implementation perspectives," *Chinese J. Mech. Eng.*, vol. 29, no. 6, pp. 1067–1073, Nov. 2016, doi: 10.3901/CJME.2016.0907.108.
- [2] M. A. Botezatu, C. Pirnau, and R. M. C. Ciocardia, "A Modern Quality Assurance System - Condition and Support to an Efficient Management," *TEM J.*, vol. 8, no. 1, pp. 125–131, Feb. 2019, doi: 10.18421/TEM81-18.
- [3] E. H. S. Oberoi, M. Parmar, and R. Mehra, "SPC (Statistical Process Control): A Quality Control Technique for Confirmation to Ability of process," pp. 666–672, 2016.
- [4] I. Madanhire and C. Mbohwa, "Application of Statistical Process Control (SPC) in Manufacturing Industry in a Developing Country," vol. 40, pp. 580–583, 2016, doi: 10.1016/j.procir.2016.01.137.
- [5] E. L. S. Teixeira, T. S. Dias, M. de O. Andrade, and A. B. S. Oliveira, "Statistical Process Control Application In Automotive Industry," 2017.
- [6] O. A. Vanli and E. Del Castillo, "Statistical Process Control in Manufacturing," in *Encyclopedia of Systems and Control*, 2014, pp. 1–7. doi: 10.1007/978-1-4471-5102-9_258-1.
- [7] P. Pathak, A. Shrivastava, and S. Gupta, "A survey on various security issues in delay tolerant networks," *J Adv Shell Progr.*, vol. 2, no. 2, pp. 12–18, 2015.
- [8] G. A. Keskin, M. Çolak, and B. Güngör, "Application of Statistical Process Control in Manufacturing Process : A Case Study in Cleaning Products Sector," pp. 544–551, 2019.
- [9] I. Madanhire and C. Mbohwa, "Application of Statistical Process Control (SPC) in Manufacturing Industry in a Developing Country," *Procedia CIRP*, vol. 40, pp. 580–583, 2016, doi: 10.1016/j.procir.2016.01.137.
- [10] B. S. Jogi, L. R. Gour, and N. Turkar, "Process Improvement Using Statistical Process Control in a Small Scale Industry," *Int. J. Trend Sci. Res. Dev.*, vol. 2, no. 5, pp. 1885–1892, Aug. 2018, doi: 10.31142/ijtsrd17144.
- [11] M. A. Abteew, S. Kropi, Y. Hong, and L. Pu, "Implementation of Statistical Process Control (SPC) in the Sewing Section of Garment Industry for Quality Improvement," *Autex Res. J.*, vol. 18, no. 2, pp. 160–172, Jun. 2018, doi: 10.1515/aut-2017-0034.
- [12] M. A. Abteew, S. K. Bhuyan, Y. Hong, and L. Pu, "Implementation of Statistical Process Control (SPC) in the Sewing Section of Garment Industry for Quality Improvement," *Autex Res. J.*, vol. 18, no. 2, pp. 160–172, Jun. 2018, doi: 10.1515/aut-2017-0034.
- [13] I. Madanhire and C. Mbohwa, "Statistical Process Control (SPC) Application in a Manufacturing Firm to Improve Cost Effectiveness : Case study," pp. 2298–2305, 2016.
- [14] U. Korat and A. Alimohammad, "A Reconfigurable Hardware Architecture for Principal Component Analysis," *Circuits, Syst. Signal Process.*, vol. 38, no. 5, pp. 2097–2113, 2019.
- [15] S. D. Bhosale, S. C. Shilwant, and S. R. Patil, "Quality improvement in manufacturing processes using SQC tools," *Int. J. Eng. Res. Appl.*, vol. 3, no. 3, pp. 832–837, 2013.
- [16] S. A. H. Lim, J. Antony, and S. Albliwi, "Statistical Process Control (SPC) in the food industry – A systematic review and future research agenda," *Trends Food Sci. Technol.*, vol. 37, no. 2, pp. 137–151, Jun. 2014, doi: 10.1016/j.tifs.2014.03.010.
- [17] P. S. Parmar and V. A. Deshpande, "Implementation of Statistical Process Control Techniques in Industry : A Review," vol. 1, no. 6, pp. 583–587, 2014.
- [18] G. Suman and D. Prajapati, "Control chart applications in healthcare: a literature review," *Int. J. Metrol. Qual. Eng.*, vol. 9, p. 5, May 2018, doi: 10.1051/ijmqe/2018003.
- [19] R. Satya Prasad, B. S. Rao, and R. R. L. Kantam, "Monitoring Software Reliability using Statistical Process Control: An MMLE Approach," *Int. J. Comput. Sci. Inf. Technol.*, vol. 3, no. 5, pp. 221–227, Oct. 2011, doi: 10.5121/ijcsit.2011.3520.
- [20] O. Bataineh and A. Al-dwairi, "Application of statistical process control tools to improve product quality in manufacturing processes," vol. 116, pp. 4023–4027, 2012, doi: 10.4028/www.scientific.net/AMM.110-116.4023.

- [21] G. Škulj, R. Vrabič, P. Butala, and A. Sluga, "Statistical Process Control as a Service: An Industrial Case Study," *Procedia CIRP*, vol. 7, pp. 401–406, 2013, doi: 10.1016/j.procir.2013.06.006.
- [22] I. I. A. and S. O. E., "The Development And Application Of Statistical Process Control Software For Higher Productivity In Manufacturing Companies," *African J. Appl. Res.*, vol. 4, no. 1, pp. 1–13, 2018, doi: 10.26437/ajar.04.01.2018.01.
- [23] M. Raheem and A. Gbolahan, "Application of Statistical Process Control in a Production Process," *Sci. J. Appl. Math. Stat.*, vol. 4, no. 1, p. 1, 2016, doi: 10.11648/j.sjams.20160401.11.
- [24] N. V. Razmochaeva, V. P. Semenov, and A. A. Bezrukov, "Methods of Automating Processes in Statistical Control and Quality Management Field," in 2019 International Conference "Quality Management, Transport and Information Security, Information Technologies" (IT&QM&IS), 2019, pp. 294–298. doi: 10.1109/ITQMIS.2019.8928441.
- [25] A.-W. Saif, "A Frame Work for the Integration of Statistical Process Control and Engineering Process Control," in 2019 Industrial & Systems Engineering Conference (ISEC), 2019, pp. 1–4. doi: 10.1109/IASEC.2019.8686557.
- [26] R. Godina and J. C. O. Matias, "Improvement of the statistical process control through an enhanced test of normality," in 2018 7th International Conference on Industrial Technology and Management (ICITM), 2018, pp. 17–21. doi: 10.1109/ICITM.2018.8333912.
- [27] T. A. Cooke and W. R. Howe, "Dynamic statistical process control limits for power quality trend data," in 2018 18th International Conference on Harmonics and Quality of Power (ICHQP), 2018, pp. 1–5. doi: 10.1109/ICHQP.2018.8378878.
- [28] Polu, A. R., Buddula, D. V. K. R., Narra, B., Gupta, A., Vattikonda, N., & Patchipulusu, H. (2021). Evolution of AI in Software Development and Cybersecurity: Unifying Automation, Innovation, and Protection in the Digital Age. Available at SSRN 5266517.
- [29] Padur, S. K. R. (2020). From centralized control to democratized insights: Migrating enterprise reporting from IBM Cognos to Microsoft Power BI. *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol.*, 6(1), 218-225.
- [30] Bitkuri, V., Kendyala, R., Kurma, J., Mamidala, V., Enokkaren, S. J., & Attipalli, A. (2021). Systematic Review of Artificial Intelligence Techniques for Enhancing Financial Reporting and Regulatory Compliance. *International Journal of Emerging Trends in Computer Science and Information Technology*, 2(4), 73-80.
- [31] Padur, S. K. R. (2019). Machine learning for predictive capacity planning: Evolution from analytical modeling to autonomous infrastructure. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 5(5), 285-293.
- [32] Attipalli, A., Enokkaren, S., BITKURI, V., Kendyala, R., KURMA, J., & Mamidala, J. V. (2021). Enhancing Cloud Infrastructure Security Through AI-Powered Big Data Anomaly Detection. Available at SSRN 5741305.
- [33] Singh, A. A. S., Tamilmani, V., Maniar, V., Kothamaram, R. R., Rajendran, D., & Namburi, V. D. (2021). Predictive Modeling for Classification of SMS Spam Using NLP and ML Techniques. *International Journal of Artificial Intelligence, Data Science, and Machine Learning*, 2(4), 60-69.
- [34] Padur, S. K. R. (2020). AI augmented disaster recovery simulations: From chaos engineering to autonomous resilience orchestration. *International Journal of Scientific Research in Science, Engineering and Technology*, 7(6), 367-378.
- [35] Reddy Padur, S. K. (2021). From Scripts to Platforms-as-Code: The Role of Terraform and Ansible in Declarative Infrastructure Rollouts. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 621-628.
- [36] Kothamaram, R. R., Rajendran, D., Namburi, V. D., Singh, A. A. S., Tamilmani, V., & Maniar, V. (2021). A Survey of Adoption Challenges and Barriers in Implementing Digital Payroll Management Systems in Across Organizations. *International Journal of Emerging Research in Engineering and Technology*, 2(2), 64-72.
- [37] Padur, S. K. R. (2018). Autonomous cloud economics: AI driven right sizing and cost optimization in hybrid infrastructures. *International Journal of Scientific Research in Science and Technology*, 4(5), 2090-2097.
- [38] Rajendran, D., Namburi, V. D., Singh, A. A. S., Tamilmani, V., Maniar, V., & Kothamaram, R. R. (2021). Anomaly Identification in IoT-Networks Using Artificial Intelligence-Based Data-Driven Techniques in Cloud Environmen. *International Journal of Emerging Trends in Computer Science and Information Technology*, 2(2), 83-91.
- [39] Padur, S. K. R. (2021). Bridging Human, System, and Cloud Integration through RESTful Automation and Governance. *the International Journal of Science, Engineering and Technology*, 9(6).
- [40] Attipalli, A., BITKURI, V., KURMA, J., Enokkaren, S., Kendyala, R., & Mamidala, J. V. (2021). A Survey of Artificial Intelligence Methods in Liquidity Risk Management: Challenges and Future Directions. Available at SSRN 5741342.
- [41] Padur, S. K. R. (2021). From Control to Code: Governance Models for Multi-Cloud ERP Modernization. *International Journal of Scientific Research & Engineering Trends*, 7(3).
- [42] Routhu, K. K. (2021). Harnessing AI Dashboards in Oracle Cloud HCM: Advancing Predictive Workforce Intelligence and Managerial Agility. *International Journal of Scientific Research & Engineering Trends*, 7(6).
- [43] Padur, S. K. R. (2021). Deep learning and process mining for ERP anomaly detection: Toward predictive and self-monitoring enterprise platforms. Available at SSRN 5605531.