Application of X-bar R Control Charts for Process Efficiency Monitoring: A Data-Driven Approach in Quality Management

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Abstract: Ensuring process efficiency and product quality remains a critical challenge in modern manufacturing, necessitating the implementation of robust methodologies for process monitoring and optimisation. Lean Six Sigma (LSS), which integrates Lean Manufacturing and Six Sigma principles, is widely adopted to enhance productivity while minimising process variability and waste. A key component of LSS is Statistical Process Control (SPC), which employs control charts to assess process stability and compliance in real time. Despite extensive research on SPC applications, existing studies often fail to systematically differentiate common cause variation from special cause variation and to identify their critical sources in industrial processes. Addressing this gap, the present study evaluates the effectiveness of X-bar R control charts as a data-driven methodology for identifying process inefficiencies. Using Minitab Statistical Software, the study analyses the adhesion parameter of Thermoplastic Polyurethane (TPU) film, a material widely used for electronic screen protection. The methodology involves constructing X-bar R control charts to monitor variability patterns, establish stability thresholds, and pinpoint critical sources of process deviations. The findings demonstrate that X-bar R control charts provide a robust framework for differentiating process variations, facilitating targeted corrective actions to enhance process stability. This research highlights the importance of statistical modelling in industrial decision-making, particularly within automated manufacturing environments. A key contribution of the study lies in its demonstration of the practical applicability of control charts in quality management and the integration of data-driven techniques for process control. Future research should investigate advanced machine learning-based SPC approaches to refine real-time decision-making and expand the applicability of control charts to dynamic and complex production systems. By reinforcing the role of statistical tools in quality engineering and operational excellence, this study contributes to the broader discourse on digital transformation in industrial process optimisation.

1 INTRODUCTION

Quality is an integral aspect in the proper and efficient functioning of production processes. In recent decades, a significant increase in its relevance has been observed [1], and multifaceted quality control has become a key element in maximising quality levels [2]. The described approach leads to building a market advantage for companies implementing activities within the described policy.

Of paramount importance is the need to combine activities aimed at improving quality, with a parallel increase in process efficiency [3]. Aiming to continuously improve productivity in the realised processes and increase the quality of manufactured products through continuous improvement, requires the implementation of specific methodologies such as Lean Six Sigma (LSS), which is an integration of Lean Manufacturing and Six Sigma. The general premise of the above-mentioned strategy is the elimination of waste, aimed at increasing productivity while reducing production costs [4-7].

It should be emphasised that in order to realise the assumptions that constitute the essence of successful LSS implementation, statistical process control (SPC), which involves the use of a wide range of indicator-based statistical methods to monitor and control process quality, becomes an extremely important aspect [8,9]. A fundamental tool within SPC are control charts, which enable the assessment of process compliance in terms of their stability and real-time performance [10-12]. The creator of control charts is considered to be Walter Shewhart [11]. Their primary purpose is to detect at an early stage undesirable trends, behaviour in the process area, which could be an initiating factor for defects or losses. The essence of the operation of control charts needs to be emphasised that they are not based on mathematical models, and the prediction of the further course of the process (future results), is based solely on process data obtained within the realised area.

The essential elements of the control chart are the boundary lines, which define the ranges of acceptable process variability. A distinction is made between: The central line, which represents the process average, as well as the upper (UCL) and lower control limits (LCL). Through simplicity of interpretation, when points on the control line fall outside the limits or when characteristic trends or other specific signals – common cause or special cause variation – are observed, it should indicate that the process is not performing as intended, and the consequence is to take intervention measures aimed at identifying and eliminating the factors creating the problem.

If, on the other hand, all measurements are within the control limits, such a situation should be interpreted as the fact that there is a common cause variation in the process, which is consistent, stable and predictable within a certain range of data, and actions aimed at reducing the variability of the process should focus on the area of identifying the sources of variability, by, among other things, understanding the cause-effect sequence of the analysed process.

Thus, for individual data, a single point outside the control limits on a Moving Range (MR) chart is classified as special cause variation, whereas for subgroup data, a point outside the control limits on a Range (R) chart indicates special cause variation. If all points remain within the control limits without significant trends or patterns, the process is considered to exhibit only common cause variation. These identification criteria are consistent with widely accepted control chart rules used to detect special cause signals.

Based on the classification according to quality characteristics, two types of control charts should be distinguished – those based on a numerical evaluation; for example: product sizes, their weight, etc. and control charts based on an alternative evaluation; for example, the number of defective pieces in a batch. An important point to note is that the most commonly used tools focused on monitoring variables when evaluating numerically are: X-means chart (sample averages are plotted), R chart (range values), S chart (standard deviation values) or S^2 chart (variance values). An example of a control chart is shown in Figure 1. UCL and LCL are included, which, based on process data, define the limits of process variability around the mean (CL).

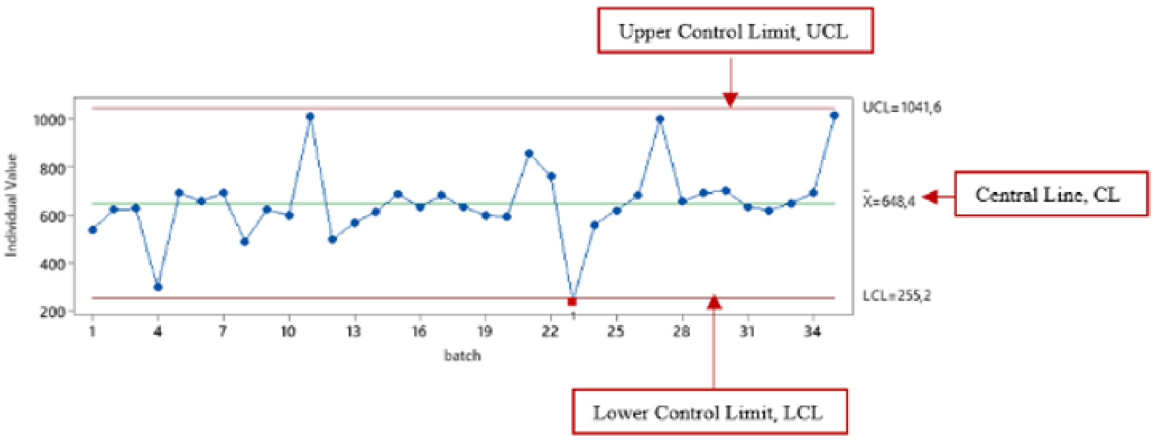

Figure 1: An example of a control chart the distribution of LCL, UCL and CL.

The ULC, LCL values determined on the control chart represent the limits of variation defined as 3 Sigma [13, 14]. The indicated value is primarily due to the fact that the use of 3 Sigma limits enables an effective distinction between common and special cause variation. In addition, it should be noted that this setting of control limits represents a balance between the risk of Type I and Type II error, i.e. over- and under-reaction to process variations. A key element is that the Sigma value is calculated differently from the classic standard deviation value, as this figure represents only its estimate. In addition, depending on the type of control chart, the Lower and Upper Control Limit values are calculated differently.

2 LITERATURE REVIEW

A literature review in the field of scientific publications shows many sources highlighting the importance of the use of control charts as tools used in the area of quality improvement, by minimising process variance [15,16].

In the article [17], the authors point out that statistical process control is a method of monitoring and improving a process through statistical analysis, with control charts as a key tool to detect changes that require intervention in the area of production processes. The publication [18] defines control charts as a basic statistical tool, and their simplicity in the area of design, using the solutions proposed by Shewhart, based on a statistical or economic criterion, significantly facilitate the interpretation of the process and the taking of specific corrective actions when we have specific signals to do so. The author [19], on the other hand, emphasises the versatility of the use of control charts by monitoring each production stage. Furthermore, the article defines control charts as the most important method of quality control.

In the article [20], the authors address issues related to the proper selection of control charts so that process control is as effective as possible; the proper identification of variability within an area of activity. The publication further provides an overview of the effectiveness of different types of control charts, such as Shewhart type and exponentially weighted moving range.

The publication [21] draws attention to the fact that the implementation of conventional Shewhart control charts can generate risks in the form of relatively longer time needed to identify small or medium process disturbances. An alternative solution to improve efficiency by modifying the control charts is therefore proposed. The importance of control charts as an essential tool in the area of statistical process control is also addressed in a publication [22]. The authors define their role in the maintenance layer and in improving the quality level of the process, and the correct use of the data is an essential element in terms of reducing variability.

Due to their significant added value, control charts are widely used in many industries [19,23]: medical [24-27], pharmaceutical [28], automotive [29], chemical [30,31] and others [32,33].

The analysis of the literature clearly indicates the validity of the use of control charts in terms of process monitoring. It should be emphasised that there is a research gap with regard to how to identify the type of variability (common cause or special cause variation) and the sources that create it. Based on the above, the research area of this publication is aimed at verifying the hypothesis that control charts X-bar R are an excellent tool for distinguishing variability, as well as defining the critical areas that are its source (common cause variation). An additional aim of the publication is to identify recommendations for strategies to deal with correctly defining types of variability and identifying their potential substrate. The activities are comprehensive and based on an analysis of the process from a cause and effect perspective.

3 METHODOLOGY

The study carried out concerned the presentation of X-bar R check sheets as a tool to identify the optimal approach, in order to identify the type of variability (common cause or special cause variation), as well as to define the potential areas constituting its source. This study included both quantitative and qualitative aspects. For the analysis of the collected process data, the statistical software Minitab 21.4.1 was used, which is an advanced statistical tool that enables a multidimensional yet in-depth analysis. It should be noted that Minitab effectively presents the aspect of diversity in terms of statistical techniques and their application in the experimental studies carried out. The software is centred around Automated Machine Learning for both binary and continuous responses, leveraging a Predictive Analytics Module [34]. Tailored for business-focused operations, it provides users with convenient methods to input statistical data, manipulate it, identify patterns and trends, and ultimately analyse the data to address real-world problems. Minitab streamlines data analysis, making it particularly suitable for statistical interpretation at the business level. It offers a variety of visual tools like histograms, boxplots, and scatterplots, enabling professionals to conduct statistical analysis more efficiently and derive insights from their data. Furthermore, it empowers users to compute descriptive statistics for their datasets.

Based on the research hypothesis, a case study focused on the supply control process of TPU (thermoplastic polyurethane) films was conducted. The adhesion parameter - the strength of the adhesive with which the film is coated - was investigated. This parameter is a key value for TPU films protecting the screens of electronic devices, so its constant control is very important.

The limitations of the inference in terms of the case study carried out may be due to several independent factors. Crucially, when investigating process variability, two lab technicians were used at the data collection stage and samples from four different material deliveries were analysed. Two samples were taken from each delivery, which were subjected to three independent measurements (each). The sampling tree created at the planning stage, together with a combination of X-bar R control charts, allows the sources of variability to be identified, as well as the area in terms of variability that most builds up the global variability of the process analysed.

In order to test the adhesion of the films, proper sample preparation becomes a key element. The material to be tested is cut in the form of strips 15 cm. long and 2.5 cm. wide. The film samples prepared in this way are glued onto 100 x 50 x 4 mm. laboratory float glass. (one batch of glass was used in the study). The adhesion force was measured using an Axis force meter, model FB on an automatic tripod, model STAH. The speed of the automatic gantry was a constant value - 20 mm./s for each run. Ambient conditions - 23.1°C ± 0.1; humidity - 60% ± 1.

4 RESEARCH RESULTS

The research carried out within the scope of this case study aims to find an answer in the area of the hypothesis, which was defined on the basis of the identified research gap. The area of results represents a broad spectrum of statistical analysis, based directly on quantitative analysis, enriched by elements of qualitative analysis. The numerical data on which the statistics focus are primary in nature.

The histogram presented in Figure 2 shows the total distribution of adhesion measurement data over three months. It should be clearly emphasised that the data included in the analysis includes the total variability of the process, which is a critical element for correct inference based on the results obtained. The lower limit of the adhesive force specification is 12N, while the value of the upper limit was set at 18N.

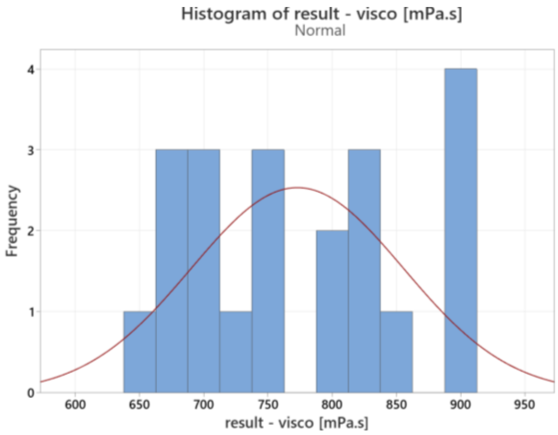

Figure 2: Histogram of the analysed values (three months).

When analysing Figure 2, it should be noted that some of the measurements obtained during the process are outside the accepted specification limits, which may pose a problem in terms of ensuring the expected quality. In addition, the distribution of the data presented in this chart reveals some differences in the context of a classical normal distribution, which should be particularly taken into account when determining further research directions and the tools to be used.

Figure 3; Time Series Plot, in contrast to Figure 2, corresponds to the distribution of the process data, taking into account their actual sequence. The data included in the Time Series Plot represent the absence of characteristic waveforms or strictly defined trends, and their arrangement is completely random, confirming that no strong external factor acted on the process, which could cause a serious problem within erroneous inference.

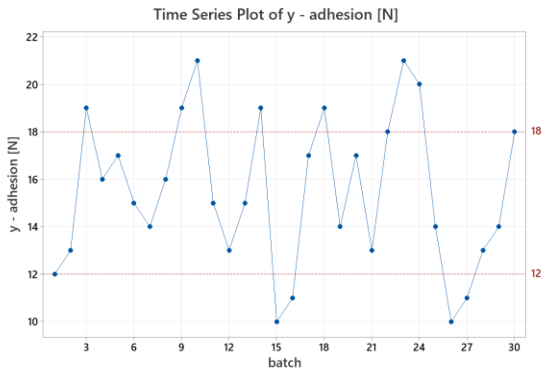

Figure 3: Time Series Plot of the analysed values (three months).

Based on the assumptions of the research study carried out, a sampling tree was prepared - Figure 4 - before proceeding to the data collection stage, which was analysed directly to define the type of variability dominating the process, as well as to identify its sources.

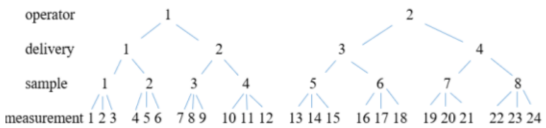

Figure 4: Sampling Tree; case study.

The sampling tree was developed with reference to the initial assumptions made - two operators in the process, four deliveries of material from which two samples were taken for testing, and each sample was measured three times.

The data acquired at the sampling stage reflects the total variability of the process and can therefore be used for further analysis. Based on the collected results, an X-bar R - Figure 5 control chart was prepared using Minitab, which enables an extensive statistical analysis to be carried out in the area of defining the parameters that constitute the purpose of this publication - determining the type of variability, as well as defining the source of variability dominating the process (operator to operator, delivery to delivery, sample to sample, measurement to measurement), taking into account the percentage of global variability. The interpretation of control charts for distinguishing the type of variation was based solely on identifying single points outside the control limits on the Range (R) chart in the analyzed case.

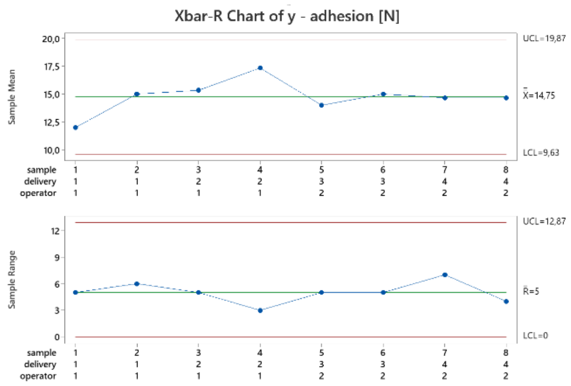

Figure 5: X-bar R control chart; adhesion.

Average of the range:

$$\bar{R} = \frac{\sum_{i=1}^{k} R_i}{k} = \frac{5+6+5+3+5+5+7+4}{8} = 5, \qquad (1)$$

where R_i is the range of the i-th subgroup and k is the number of subgroups.

Average of averages:

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{k} \bar{x}_i}{k} = \frac{12.00+15.00+15.33+17.33+14.00+15.00+14.67+14.67}{8} = 14.75\,, \qquad (2)$$

where $\bar{x}_i$ is the average of the i-th subgroup and k is the number of subgroups.

Upper Control Limit (UCL) and Lower Control Limit (LCL) for R chart:

$$UCL_R = D_4 \cdot \bar{R} = 2.575 \cdot 5 = 12.87, \qquad (3)$$

$$n < 7,\ LCL_R = 0, \qquad (4)$$

$$n \geq 7,\ LCL_R = D_3 \cdot \bar{R}. \qquad (5)$$

The value of the constant D_4 for the subgroup size k=3, is 2.575.

Upper Control Limit (UCL) and Lower Control Limit (LCL) for X-bar chart:

$$UCL_{\bar{x}} = \bar{\bar{x}} + A_2 \cdot \bar{R} = 14.75 + 1.023 \cdot 5 = 19.87, \qquad (6)$$

$$LCL_{\bar{x}} = \bar{\bar{x}} - A_2 \cdot \bar{R} = 14.75 - 1.023 \cdot 5 = 9.63. \qquad (7)$$

The value of the A_2 constant for the subgroup size k=3, is 1.023.

Determining the percentage distribution of individual sources of variability in terms of global variability makes it easy to identify which source of variability is the dominant source in the process and which one should be addressed first:

$$100\% = \hat{\sigma}^2{}_{total} = \hat{\sigma}^2{}_{measurement\ to\ measurement} + \hat{\sigma}^2{}_{sample\ to\ sample} + \hat{\sigma}^2{}_{delivery\ to\ delivery} + \hat{\sigma}^2{}_{operator\ to\ operator}. \quad (8)$$

Variability: measurement to measurement:

$$\hat{\sigma}^2{}_{measurement\ to\ measurement} = \left(\frac{\bar{R}}{d_2}\right)^2 = \left(\frac{5}{1.693}\right)^2 \approx 8.72 \quad (9)$$

where d_2 is a constant value, which for a subgroup of 3 is 1.693. The value of $\bar{R}$ (5), is read from the R chart created by "wrapping" the sampling tree and calculating the new parameters.

Variability: sample to sample:

$$\hat{\sigma}^2{}_{sample\ to\ sample} = \left(\frac{\bar{R}}{d_2}\right)^2 - \frac{\hat{\sigma}^2{}_{measurement\ to\ measurement}}{3} = \left(\frac{1.5}{1.128}\right)^2 - \frac{8.72}{3} \approx -1.14 \quad (10)$$

where d_2 is a constant value, which for a subgroup of 2 is 1.128. The value of $\bar{R}$ (1.5), is read from the R chart created by "wrapping" the sampling tree and calculating the new parameters.

Since the obtained sample-to-sample variability score according to the above calculation reached a negative value, it is necessary to assume that it is 0.

Variability: delivery to delivery:

$$\hat{\sigma}^2{}_{delivery\ to\ delivery} = \left(\frac{\bar{R}}{d_2}\right)^2 - \frac{\hat{\sigma}^2{}_{sample\ to\ sample}}{2} - \frac{\hat{\sigma}^2{}_{measurement\ to\ measurement}}{3\cdot 2} = \left(\frac{1.5}{1.128}\right)^2 - 0 - \frac{8.72}{6} \approx 0.32\ , \quad (11)$$

where d_2 is a constant value, which for a subgroup of 2 is 1.128. The value of $\bar{R}$ (1.5), is read from the R chart created by "wrapping" the sampling tree and calculating the new parameters.

Variability: operator to operator:

$$\hat{\sigma}^2{}_{operator\ to\ operator} = \left(\frac{\bar{R}}{d_2}\right)^2 - \frac{\hat{\sigma}^2{}_{delivery\ to\ delivery}}{2} - \frac{\hat{\sigma}^2{}_{sample\ to\ sample}}{2\cdot 2} - \frac{\hat{\sigma}^2{}_{measurement\ to\ measurement}}{3\cdot 2\cdot 2} = \left(\frac{0.33}{1.128}\right)^2 - \frac{0.32}{2} - 0 - \frac{8.72}{12} = 0.086 - 0.16 - 0 - 0.73 \approx -0.80 \quad (12)$$

where d_2 is a constant value, which for a subgroup of 2 is 1.128. The value of $\bar{R}$ (0.33), is read from the R chart created by "wrapping" the sampling tree and calculating the new parameters.

Since the obtained sample-to-sample variability score according to the above calculation reached a negative value, it is necessary to assume that it is 0.

Based on calculations of the significance of individual types of sub-variability in terms of global variability, the dominant source is measurement to measurement variability - 96.46%, a small fraction is delivery to delivery variability - 3.54%, while the remaining sub-variabilities are not statistically significant.

5 DISCUSSION

The case study provides a valuable resource in terms of the use of X-bar R control charts and the direct benefits of their implementation. The statistical analysis provides important data on the approach to identifying the type of variability and which factor is key to shaping the holistic variability of the process. Distinguishing the types of variability has a fundamental impact on defining the right course of action in the context of variance reduction, while identifying the critical area that is most responsible for building total process variability is a fundamental aspect as an element that can lead to holistic variability reduction. It should be noted that any case study involves certain limitations that may result in incomplete objectivity in adequately representing the area of knowledge studied.

Publications [35-38] point out that the primary objective in terms of implementing control charts is to minimise the costs resulting from process control, as well as to increase the quality of products and services. On the other hand, the article [40] points out that X-bar and R chart are effective tools in detecting signals that may indicate that a process is out of control.

In the article [38], the authors emphasise that the X-bar R control charts is widely used in quality management systems, but attention should be paid to the likelihood of false alarms due to its direct limitations. Publications [35-38] indicate that X-bar, which are used to control the process mean, and R charts, which are responsible for controlling variance, do not have an adequate level of sensitivity to respond to small changes in process parameters. Instead, the authors [35] propose the use of the adaptive non-central chi-square statistic chart, which has a significantly higher level of performance compared to standard control charts.

A number of literature sources indicate a trend towards the development of control charts, aiming to develop robust tools that eliminate the risk of detecting signals lacking statistical significance. In [41], the authors highlight the fact that X-bar and R chart are extremely useful for controlling and detecting causes generating adverse effects in terms of process variability, pointing out that in order to increase the sensitivity of a standard control chart, it is necessary to include an auxiliary variable in the analysis. The content of the article [42] focused on the aspect of improving the effectiveness of signalling variance increases with respect to the classic R chart (Shewhart), and the values obtained showed that an R chart with variable parameters is more sensitive to variance increases.

Moreover, the findings of this study, particularly regarding the use of statistical tools for monitoring and controlling variations in industrial processes, align with the broader methodological approaches applied in other domains. For instance, research on electronic administration systems has highlighted the role of digitalisation in improving process efficiency and ensuring regulatory compliance, which is conceptually related to process control and quality assurance mechanisms in industrial settings [43]. Similarly, studies on anti-money laundering strategies in digital economies have demonstrated the importance of systematic risk detection and mitigation, paralleling the approach used in identifying variability sources within production processes [44]. In addition, cybersecurity research underscores the necessity of continuous monitoring and early detection of anomalies, reinforcing the importance of real-time statistical control in quality management [45; 46]. Furthermore, methodological advancements in experimental design and factorial analysis for quality management provide additional insights into improving the precision of variance detection [47]. Lastly, research on artificial intelligence in process optimisation suggests that machine learning-driven SPC techniques could enhance the predictive capabilities of control charts, providing a future direction for expanding the applicability of X-bar R charts in automated manufacturing environments [48].

The literature sources covered in this chapter highlight the importance of control charts, pointing to the potential for problems in terms of the proper detection of factors that generate small changes in process parameters (X-bar R). The analysis of the literature indicates that there is a lack of detailed description of how to proceed in the interpretation of X-bar R control charts in the context of defining the type of variation, identifying critical areas corresponding to potential sources of variation, as well as indicating the percentage distribution of partial variation on a global basis.

6 CONCLUSIONS

The statistical analysis carried out within the scope of this case study provides a broad spectrum of information in terms of the hypothesis set up based on the identified research gap. It should be mentioned that the analysis carried out indicates the importance of distinguishing common cause and special cause variation, as an overarching element that initiates actions aimed at minimising variability, and also includes an aspect related to the identification of the source or sources of partial variation, which are critical in terms of global process variability.

The article confirms the research hypothesis, highlighting the importance of using the control charts X-bar R. The R chart makes it possible to assess stability in the area of process variability. Furthermore, it provides important information by indicating the type of variability present; common cause or special cause variation. Correctly distinguishing the type of variation defines the subsequent workflow related to minimising the total variation. If special cause variation is identified in the process, it becomes necessary to take immediate, short-term action. In the case of common cause variation, on the other hand, it is necessary to first understand the cause-effect sequence of the process, an important aspect being then to define the areas from which the greatest variability arises. In identifying the area of variation, the X-bar plays an invaluable role, being responsible for monitoring changes at a central level, thus making it possible to pinpoint the origin of the source of variation, which in turn significantly facilitates the identification of the process factors that can have a decisive influence on its creation. X-bar and R-control charts are particularly useful in batch and continuous production, where continuous quality monitoring is key to maintaining standards and minimising waste.

Future research directions should focus on enhancing the effectiveness of statistical process control by integrating artificial intelligence and machine learning algorithms. The development of predictive SPC models based on historical data and real-time sensor inputs could provide more accurate anomaly detection and facilitate proactive decision-making. Additionally, expanding the application of X-bar R control charts to dynamic and adaptive manufacturing environments, such as Industry 4.0 and smart factories, would allow for a deeper understanding of process behaviour under varying conditions. Further interdisciplinary studies can explore the correlation between statistical process control and digital transformation trends, including blockchain-based traceability in supply chains and the use of cyber-physical systems for real-time quality monitoring. Moreover, addressing the limitations of traditional SPC methods by developing hybrid approaches that combine statistical techniques with computational intelligence can open new avenues for improving production efficiency and reducing defects. Lastly, applying control charts in non-industrial sectors, such as healthcare, finance, and environmental monitoring, could provide valuable insights into variability management and contribute to a broader adoption of SPC methodologies in diverse domains.

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