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Research Article

Application of the Pareto Principle in Quality Management through an Integrated Model of Statistical Process Control and Design of Experiments

Maciej Kardas

Abstract. Quality management in production processes faces ongoing challenges related to variability and process stability, particularly in the context of complex manufacturing environments. Despite extensive use of Statistical Process Control (SPC) and Design of Experiments (DoE), there remains a gap in integrating these approaches with the Pareto Principle for effective decision-making and continuous improvement. This study aims to address this gap by evaluating the combined application of the Pareto Principle with SPC and DoE in managing production quality. The case study was conducted in a single-component paint manufacturing company, focusing on dynamic viscosity as a key quality parameter. The research methodology included process data compliance evaluation, identification of variability sources, measurement system analysis, and the development of a fractional experimental design. The results revealed that operator performance was the primary source of variability. Among the studied factors, maintenance time and temperature during thickener activation had the most significant impact on process stability. Optimising these parameters led to a substantial reduction in natural variability, keeping viscosity within specification limits. The findings suggest that the integrated SPC-DoE-Pareto model provides an effective framework for addressing key sources of deviation and improving quality management decisions. This approach not only enhances process stability but also aligns with the principles of continuous improvement. Further research could explore the broader applicability of the SPC-DoE-Pareto integration in different industries and its impact on long-term process performance. Additionally, investigating the role of advanced automation and machine learning in supporting these models could offer new avenues for improvement in quality management.

Keywords: quality management, Pareto principle, statistical process control, design of experiments, parameter optimisation, machine learning, optimising.

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1. Introduction

Quality is characterised as a multifaceted concept encompassing product compliance with specifications, consistency of production processes, and overall satisfaction of customer needs. The evolution of quality management has been significantly influenced by technological progress within the framework of Industry 4.0 and the emerging paradigms of Industry 5.0 [1–9]. The concept of quality is not static but is strongly linked to a dynamic process aimed at integration across multiple dimensions—both human and technological—which translates into increased operational performance, defined as the ability to maximise productivity while minimising resource use and waste [10]. It includes the ratio of output achieved to resources invested, emphasising the optimisation of processes and resource use in order to enhance competitive advantage [11, 12].

The transition from traditional quality control, representing a reactive approach, to modern quality management systems reflects a broader understanding of quality as a holistic concept. Today, it engages all stakeholders in the production process—from the selection of raw materials to the delivery of the final product—thereby intensifying proactivity [13].

The integration of technologies embedded within the framework of Industry 4.0, such as the Internet of Things, big data analytics, and artificial intelligence, is transforming existing approaches to quality management [14]. As a result, it is now possible to monitor production processes in real time and make decisions based on collected data. For example, the implementation of statistical process control (SPC) and predictive analytics allows for the early detection of potential problems, thereby minimising losses and increasing overall efficiency. Additionally, the use of digital twins contributes to improved accuracy in quality assessment and facilitates continuous process improvement [15].

Quality management is a complex issue involving systematic actions aimed at ensuring that the products and services offered by an organisation meet defined standards and respond to diverse customer needs. It constitutes an integral element of both the strategic and operational dimensions of an enterprise. The implementation of effective quality management enables the creation of sustainable competitive advantage, optimisation of production processes, and support for sustainable development.

The evolution of quality management has been shaped by numerous theories and practices. Initially, the focus was on basic quality control; over time, advanced strategies such as Total Quality Management (TQM), Lean, and Six Sigma were developed. A significant role in process standardisation has been played by the implementation of ISO standards, including ISO 9001, which is globally recognised as a benchmark for ensuring product and process quality [16]. It is based on a process approach, risk management, and the necessity of top management involvement in implementing quality strategies. A strong focus on the customer requires organisations to clearly define quality objectives, monitor process performance, and undertake corrective actions, leading to the fulfilment of customer expectations and the improvement of operational efficiency [17].

A significant contribution to the development of quality management was made by the Italian economist Vilfredo Pareto, who observed that wealth in society is unevenly distributed—80%

of the wealth is held by 20% of the population [18]. Joseph M. Juran adapted this principle to the field of quality, indicating that 20% of causes account for 80% of quality problems [19]. This made it possible to identify the key factors affecting quality and focus efforts on their elimination. In addition, the concept of the quality trilogy was introduced, encompassing quality planning, quality control, and quality improvement [20]. Quality planning involves identifying customer needs and creating products that meet these requirements. Quality control consists of monitoring and evaluating the performance of processes and products to ensure compliance with standards. Quality improvement corresponds to the continuous optimisation of processes aimed at increasing efficiency by identifying and eliminating areas that require enhancement [21]. Juran's concept provides a framework for the application of statistical process control and design of experiments [22]. He also emphasised the importance of top management's involvement in improving quality within an organisation [19].

W. E. Deming, continuing the development of quality concepts, presented 14 management principles in the 1980s that became the foundation of the modern approach to quality. His philosophy defines quality as an integral element of a company's strategy aimed at long-term success [23]. He emphasised customer orientation, the role of leadership, employee engagement, and continuous improvement. The TQM philosophy, stemming from his concepts, is not merely a set of tools but a comprehensive strategy requiring a change in organisational culture and full involvement of all employees [24].

Contemporary quality management is strongly linked to the development of digital technologies, known as Industry 4.0, the fourth industrial revolution. It is characterised by the integration of technologies such as artificial intelligence (AI) and the Internet of Things (IoT) with production processes, transforming the way organisations operate [25]. The success of a company's digital transformation depends on implementing agile, process-oriented approaches that utilise digital tools and data analytics [26]. The key objective is to adapt organisational strategies to the dynamically changing needs of customers and market conditions through proactive prediction of potential problems and preventive actions [27]. The integration of advanced technologies with traditional quality management tools increases the ability to collect and analyse large amounts of data, enabling more informed decision-making [28].

Strategies such as Lean and Six Sigma play an important role in quality management, introducing a structured approach to process improvement. Lean focuses on eliminating waste and optimising value flow, while Six Sigma uses statistical analysis to minimise process variability and improve product quality [29]. The use of these philosophies allows organisations to increase operational efficiency and better meet customer needs.

In recent years, quality management has become an important element of organisational practice. This trend reflects the growing importance of quality in the context of achieving competitive advantage and customer satisfaction in a rapidly changing business environment. Quality management is based on a systematic approach aimed at ensuring that all processes, services, and products not only meet but often exceed customer expectations. It is characterised by a set of principles and practices that guide an organisation in the right direction. Each concept offers unique theoretical frameworks and tools for improving quality and efficiency. Regardless of their specific characteristics, all of these approaches aim towards the same goal: creating value for both customers and stakeholders.

Modern organisations operate in an increasingly complex environment characterised by a high level of competitiveness and rapidly changing market requirements. The ability to deliver products and services of the highest quality has become a key differentiator and an essential factor ensuring an organisation's survival and growth. Understanding and effectively implementing quality management concepts is therefore an indispensable aspect of contemporary management.

The philosophical approach to quality emphasises the relationship between quality and quantity, indicating that quality results from the attributes or characteristics defining the essence of an object, whereas quantity refers to measurable aspects that give structure to these characteristics. This relationship is particularly significant in the context of quality management in production processes.

Various philosophical doctrines suggest that quality is not solely an inherent characteristic but is defined and assessed through quantitative indicators. In the production domain, the concept of quality holds critical importance—it cannot be treated as an abstraction; it must be measurable in order to meet defined standards.

When analysing definitions of quality, it is worth focusing on continuous improvement in all areas, with the aim of enhancing products, processes, services, and relationships with stakeholders [30]. In this way, the perspective aligns with the broader philosophical discourse on quality, which is not limited to meeting established standards but also supports an environment conducive to development. Quality can be perceived as a dynamic process requiring organisational commitment to the pursuit of excellence, suggesting that an organisation should adopt quality orientation as a fundamental element of its philosophy. As a result, it becomes possible to increase efficiency across various aspects of its operations.

Quality constitutes an integral element of enterprises, their processes, and their products. The simplest definition of quality indicates that it is a set of characteristics and properties of products, services, and processes that meet specific guidelines and satisfy potential needs [31]. Quality is also recognised as a measure of an enterprise's operational effectiveness. A key issue is the comparison of quality and productivity, as well as their interrelationship from a process optimisation perspective. Achieving a high level of productivity may sometimes require lowering the quality of processes or products. Conversely, increasing quality may lead to reduced productivity. These relationships highlight the need for process optimisation to ensure a balance between quality and productivity [32].

Today, quality is recognised as one of the key factors in building an organisation's competitive advantage in the global market. In recent years, its perception and role have undergone a significant transformation. From simple inspection and quality control methods, through the development of quality assurance systems, to modern quality management concepts, a continuous evolution in the approach to this issue can be observed [33]. The focus on consistently meeting standards for specific products or services defines quality in terms of reliability and uniformity. In the field of production and service delivery, the systematic use of data and statistical methods is a key element of maintaining and improving quality. The application of statistical tools, such as scatter plots or regression lines, can significantly enhance

real-time quality management, directly contributing to increased operational efficiency. Statistical methods also play an important role in quality control, enabling problem-solving and decision-making regarding the number of defective items produced in the manufacturing process [34].

2. Literature Review

Quality constitutes a key element in the functioning of every organisation, influencing operational performance, customer satisfaction, and overall business outcomes. Quality Management Systems (QMS) play a crucial role in ensuring that products and services meet or exceed customer expectations, thereby fostering the development of a strong brand and mutual trust. An efficiently operating QMS contributes to the minimisation of defects and the enhancement of customer satisfaction, influencing loyalty and the long-term growth of the enterprise [35].

Research indicates that effective quality management significantly improves quality and safety outcomes, emphasising the importance of a customer-oriented approach [36]. An essential issue is the integration of quality management practices with supply chain management in order to optimise operational performance. Muthukrishnan highlights that the implementation of a quality management system has a positive impact on organisational performance, particularly in terms of customer satisfaction and the reduction of quality-related costs [37]. Similar conclusions were drawn by Saragih et al., who emphasised the need for a holistic approach to quality encompassing all operational areas of the organisation, thereby significantly affecting overall company performance [38].

Studies conducted by Dong and Zhang demonstrate that a robust business environment, characterised by effective quality management practices, has a significant impact on organisational development and the achievement of sustainable growth [39]. The quality of the business environment is particularly important for small and medium-sized enterprises, where political factors—such as government support for entrepreneurship and legal regulations—shape its overall perception [40].

The development of business quality is also closely linked to the identification of customer requirements, directly influencing the competitiveness and innovativeness of enterprises. Sectoral differences result in varying perceptions of the factors determining quality, which is particularly relevant for shaping operational strategies in small and medium-sized enterprises [41].

The multidimensional nature of quality makes it a key factor in service delivery, as well as in building trust and commitment in business relationships. Consequently, it contributes to improving the long-term performance of the organisation. Quality, alongside trust and commitment, becomes a fundamental element in shaping stable and enduring relationships, forming the basis for market success and competitiveness.

In addition to service and operational quality, increasing attention is being paid to data quality management, which represents a critical value in improving business processes. Panahy et al. indicate that high data quality is a key factor in enhancing process efficiency, whereas low data

quality may lead to incorrect analyses and conclusions, thereby hindering improvement efforts [42].

Quality affects various areas of organisational functioning, influencing both internal processes and levels of customer satisfaction. In the manufacturing context, the implementation of quality control tools, such as Statistical Process Control (SPC), enables effective monitoring and continuous process improvement, thereby enhancing efficiency and product quality [34].

In software development, quality requirements play a crucial role in determining system success, and their importance may vary depending on project objectives and the roles of team members. The proper definition and fulfilment of these requirements are essential to ensuring that the final product meets user expectations and achieves intended objectives [43]. From a financial perspective, quality should be regarded not as an external obligation but as a source of potential economic benefits. The costs associated with maintaining quality standards should form part of a carefully designed strategy aimed at maximising long-term profitability. The effectiveness of implemented quality systems should be systematically compared with the costs incurred across all operational levels and throughout the product life cycle, thereby enabling cost optimisation and supporting sustainable organisational development [44].

The importance of quality across organisational domains is multifaceted, encompassing process efficiency, customer satisfaction, service quality, and data management. The integration of quality management systems with operational activities is essential for building competitiveness and achieving sustainable business success. In the context of increasing market dynamism and the growing complexity of the business environment, prioritising quality across all aspects of enterprise operations becomes fundamental to long-term growth.

The synergy resulting from the parallel implementation of Statistical Process Control, Design of Experiments, and the Pareto Principle represents a critical component of quality management, offering a comprehensive approach to controlling process parameters and product characteristics. Although SPC, DoE, and the Pareto Principle individually contribute to improving efficiency and effectiveness, their simultaneous application generates a synergistic effect [45].

SPC employs statistical techniques to monitor and control processes, enabling the identification of specific events and distinguishing between common and special cause variation. This allows organisations to detect deviations from expected values and promptly implement corrective actions [46]. Design of Experiments complements SPC by systematically analysing the influence of multiple variables on process outcomes, thereby enabling the identification of optimal operating parameters and supporting informed decision-making regarding process adjustments and improvements [47].

The Pareto Principle, commonly referred to as the 80/20 rule, completes this integrated approach by assuming that a relatively small number of causes (approximately 20%) are responsible for the majority (approximately 80%) of effects. It is widely used to prioritise issues requiring attention within processes [48]. This principle enables organisations to allocate resources more efficiently by focusing on the most critical areas, thereby enhancing overall quality performance.

The Pareto Principle also supports a more structured approach to problem-solving within Statistical Process Control. The use of Pareto charts allows organisations to visually represent the relative importance of various factors, facilitating prioritisation within teams. Data visualisation not only enhances decision-making but also promotes a culture of continuous improvement, encouraging teams to focus on the most impactful areas first [49]. The accurate identification of key issues enables the implementation of targeted interventions, delivering significant improvements in quality and process optimisation [50–56].

Recent studies demonstrate that the Pareto Principle continues to evolve across various domains. For instance, Funke et al. present algorithms for calculating the Pareto sum of Pareto sets in bi-criteria optimisation problems, which are relevant for improving production process quality. Their findings illustrate how the application of the Pareto Principle can lead to optimal solutions under resource constraints, offering innovative approaches to data optimisation across industries [57].

In the economic context, Gali et al. analyse the effectiveness of the Pareto Principle in voting rules, demonstrating its broader applicability in decision-making processes. Furthermore, the same study introduces an approach to adaptive thresholding in Constant False Alarm Rate (CFAR) detection using the Pareto distribution, highlighting its relevance in data analysis and quality control systems [58].

The Pareto Principle is also applied in multi-objective optimisation, as demonstrated by Nikolakakou, who examined how constraints shaping the Pareto front influence solution quality in project management contexts. This principle is therefore instrumental in identifying critical resources and processes requiring prioriterisation [52].

Beyond resource allocation and problem-solving, integrating the Pareto Principle with SPC data analysis enhances the overall effectiveness of quality management systems. Bommier and Zuber highlight that its application in economic contexts enables optimal outcomes under constrained resources [50, 59].

The synergy between SPC and the Pareto Principle also extends to the development of control charts and other SPC tools. Incorporating the Pareto Principle into their design and interpretation enhances the detection of significant changes in process performance. Dever et al. demonstrate that SPC can be effectively applied across organisational functions by focusing on key variables identified through Pareto analysis, thereby improving responsiveness to quality issues [60].

Similar insights arise from the application of the Pareto Principle in experimental design. In DoE, identifying variables with the greatest impact on outcomes is fundamental. Wang et al. emphasise the importance of reducing variability by prioritising key variables, which aligns closely with the Pareto Principle and contributes to improved performance with reduced complexity [61].

The application of the Pareto Principle in experimental design thus provides a multidimensional framework for optimisation, enabling more effective decision-making based on empirical results.

The synergy between SPC, the Pareto Principle, and DoE is particularly significant within an integrated continuous improvement model. SPC is used to monitor key performance indicators (KPIs) identified through Pareto analysis, while DoE enables the testing of hypotheses derived from SPC data. The Pareto Principle can also be applied at the experimental design stage, directing focus towards the most influential factors. This integration creates a feedback loop that enhances the effectiveness of improvement processes.

As with individual approaches, the successful implementation of the integrated model requires a transformation in organisational culture. Leadership plays a crucial role in fostering a culture of continuous improvement, promoting learning from failure, and encouraging data-driven decision-making [62]. Training programmes that equip employees with the skills necessary to apply SPC, understand the Pareto Principle, and utilise DoE effectively are essential for successful implementation.

Furthermore, the integration of SPC, the Pareto Principle, and DoE aligns with the principles of Lean Six Sigma. Lean focuses on waste reduction and process efficiency, while Six Sigma emphasises variability reduction and quality improvement. Their combined application provides a comprehensive framework for enhancing process performance and product quality.

The practical implementation of this integrated approach involves several structured steps. Organisations should first assess whether process data fall within acceptable tolerance limits. If so, monitoring is sufficient; otherwise, it becomes necessary to identify sources of variability. The Pareto Principle facilitates the identification of critical causes, guiding the DoE phase towards targeted experimentation. The results obtained enable the identification of key influencing factors, while reapplying the Pareto Principle ensures focus on the most significant elements.

The conclusions drawn from the reviewed literature suggest that integrating SPC, DoE, and the Pareto Principle may significantly enhance process optimisation, forming the basis for the research hypotheses outlined below.

The synergistic application of Statistical Process Control, Design of Experiments, and the Pareto Principle provides a robust framework for process optimisation. By leveraging the strengths of each approach, organisations can achieve substantial improvements in quality and efficiency. This integration enables a deeper understanding of process dynamics and supports targeted interventions that contribute to cost reduction and increased customer satisfaction.

A review of the scientific literature reveals a lack of comprehensive studies integrating the Pareto Principle, SPC, and DoE into a unified model. Existing research predominantly focuses on their independent application, limiting the understanding of complex cause-and-effect relationships and their practical implications. Studies addressing their combined application remain scarce and often lack detailed methodological guidance [63]. Moreover, much of the literature is theoretical, with limited empirical validation based on real-world case studies.

Although extensive research exists on the implementation of SPC and DoE across various industries, studies examining their integrated application within systematic quality management frameworks remain limited [64–66]. Similarly, the Pareto Principle, despite its widespread use, has not been sufficiently incorporated into integrated SPC–DoE models [48, 67].

Based on the above, the aim of this study is to determine the impact of applying the Pareto Principle in combination with an integrated SPC–DoE model on the quality management of production processes, with particular emphasis on identifying and controlling the primary sources of variability.

Accordingly, the following research hypotheses are proposed:

Hypothesis 1: The implementation of the Pareto Principle, in conjunction with an integrated SPC–DoE model, contributes to the optimisation of quality management in production processes by enabling the effective identification and control of key sources of variability.

Hypothesis 2: Increasing measurement system resolution and precision, as well as operator interchangeability, enhances the accuracy of decision-making in quality management.

3. Data and Methods

The subject of this study was the analysis of the effectiveness of applying the Pareto Principle to the quality management of production processes in combination with an integrated model incorporating Statistical Process Control (SPC) and Design of Experiments (DoE). The research focused on assessing the impact of these tools on reducing variability in process parameters and optimising product quality.

The data used in the analysis were derived from the production process of a single-component paint carried out in an enterprise classified as large in accordance with the European Commission guidelines. This enterprise meets the criteria of employing more than 250 employees, having an annual turnover exceeding EUR 60 million, or a balance sheet total above EUR 50 million [68].

The case study focused on reducing variability in the production process, in which the key quality parameter was dynamic viscosity. Maintaining this parameter within the specified limits constituted a prerequisite for ensuring that the product complied with the adopted customer requirements. Owing to the excessively wide range of obtained results, it was necessary to undertake actions aimed at understanding the cause-and-effect relationships and determining the influence of factors and interactions on the process. Dynamic viscosity, defined as the resistance to paint flow, is affected, inter alia, by shear rate, temperature, and time [69].

In this study, a proprietary quantitative approach based on the Pareto Principle was applied within the framework of an integrated model of Statistical Process Control and Design of Experiments, the structure of which is presented in Figure 1.

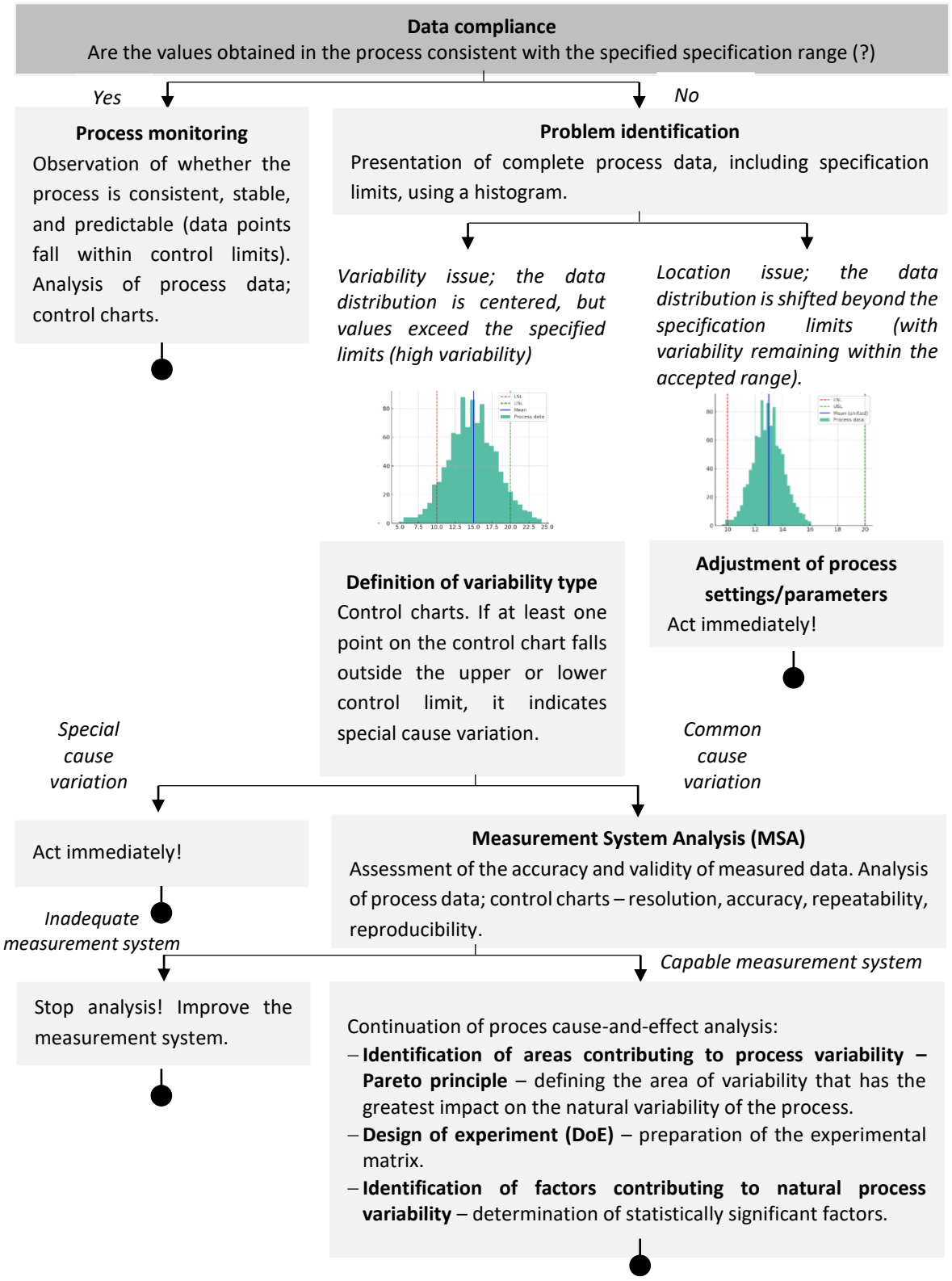


Figure 1. Schematic of the Integrated Model of Statistical Process Control and Design of Experiments Using the Pareto Principle.
Source: Developed by the Author.

The overarching objective of implementing the integrated model in conjunction with the Pareto Principle was to improve quality and ensure the continuous enhancement of the production process. The primary data were derived from a case study based on the interpretation of values obtained in real time. The project assumed the proper collection of data through a designed experiment and a thorough understanding of cause-and-effect relationships in order to identify the most appropriate parameters influencing effective quality management.

The first stage focuses on assessing data compliance, that is, verifying whether the values obtained in the process meet the established specifications. Based on this assessment, appropriate actions—either monitoring or preventive—are undertaken. The evaluation employs IMR (individual–moving range) control charts, histograms, and, where applicable, potential process capability indicators (Cp, Pp) and actual capability indices (Cpk, Ppk). Each of these tools supports a detailed analysis of the process and its performance.

In the I chart (individual chart), the lower (LCL_I) and upper (UCL_I) control limits are determined. Analysing the distribution of data relative to these limits enables the identification of appropriate actions. The MR (moving range) chart additionally indicates whether the short-term variability of the process is consistent, stable, and predictable [65, 70].

Depending on the results obtained, the second stage may involve monitoring process data to assess stability (variability), particularly when the values fall within the accepted specification range. As in the initial stage, the data are analysed using IMR charts.

If points on the I chart fall outside both the specification limits and the defined control limits, further analysis is required to identify the source of the problem. In such cases, the parallel interpretation of data distribution using the MR chart is essential, as points outside the limits indicate the presence of special cause variation [71].

When a breach of control limits is identified, the next step is to define the type of problem. Visualisation of the complete dataset using a histogram allows for an assessment of its distribution relative to the specification limits. If the distribution is shifted beyond the accepted limits while variability remains low, this indicates a location problem. Conversely, if the distribution is centred but some values exceed specification limits, a variability problem is present.

In the case of a location problem, corrective actions are relatively straightforward and typically involve eliminating the external cause of the process shift or adjusting process parameters.

When a variability problem is identified, it is necessary to determine its type. As in previous stages, this is achieved using graphical methods, particularly the MR control chart.

If at least one point lies outside the LCL_{MR} or UCL_{MR}, this indicates the presence of special cause variation, which requires immediate intervention. Such variation is typically associated with external factors not directly related to the process. In these cases, attempting to analyse the cause-and-effect structure, as would be done for common variation, may result in an inefficient use of time and financial resources.

If all points fall within the limits defined by LCL_{MR} and UCL_{MR}, the process exhibits common (natural) variation. Reducing this type of variation requires identifying root causes. Immediate corrective action in such cases may lead to over-adjustment and potentially increase process variability.

Once the type of variability has been identified, it is necessary to ensure the correctness of data collection, which requires verification of the measurement system. Since every measurement constitutes a process, it must be assessed whether its variability is significantly lower than that of the analysed process. Excessive variability in the measurement system may result in inaccurate parameter estimation and erroneous conclusions.

Measurement system analysis is conducted using $\bar{X}$–R (mean–range) control charts. The $\bar{X}$ chart indicates the precision of the measurement system and the repeatability and reproducibility of operators, while the R chart provides information on resolution and potential special causes [72–73].

If the measurement system does not meet the required standards in terms of resolution, repeatability, or reproducibility, the analysis must be suspended until improvements are implemented.

If, however, the measurement system is deemed adequate, the next step is to identify the area that most significantly contributes to process variability. This is achieved through quantitative analysis, supported by proper process mapping. Further analyses include practical methods (box plots), graphical tools ($\bar{X}$ control charts), and quantitative techniques (variability distribution analysis), all based on sampled data. These approaches are complementary and mitigate the limitations of individual methods.

Based on the identified dominant area, a designed experiment (DoE) is conducted to evaluate the factors influencing variability—a process referred to as data cascading [74]. The appropriate selection of factor levels is critical. The results of the DoE enable the identification of main effects and interactions, providing deeper insight into cause-and-effect relationships within the process.

Subsequently, scatter plots and time series analyses are used to determine whether external disturbances occurred during the experiment that may have affected the results [75]. These visualisations also help identify the presence of special cause variation within the experimental domain. An important component of the analysis is the interpretation of the Pareto chart of standardised effects, which highlights the most influential factors and interactions affecting variability. Main effects plots illustrate how changes in factor levels influence the measured response.

Within the experimental framework, it is essential to emphasise the importance of effective disturbance management. The implementation of appropriate control strategies reduces the risk of erroneous results and enhances the validity and reliability of conclusions.

The data analysis was performed using the statistical software package Minitab 21.4.1, which provides advanced tools for conducting analyses with a high degree of numerical accuracy.

4. Results

The study applied an integrated model of Statistical Process Control and Design of Experiments, incorporating the Pareto Principle, in order to optimise and enhance the effectiveness of quality management through a comprehensive understanding of cause-and-effect relationships underlying the implemented actions. A detailed characterisation of the process was undertaken, beginning with the identification of variability-generating areas and concluding with the verification of experimental results.

The process data used in the study reflected the actual variability observed in the production of single-component paint. An in-depth analysis enabled effective process control aimed at minimising the adverse impact of variability on the product's dynamic viscosity.

4.1. Data Compliance Analysis and Identification of the Type of Variability Problem

Data compliance analysis constitutes a key component of the proposed model, as it enables the identification of the type of problem—whether related to process location or variability—within the analysed case. This analysis is based on the distribution of values presented using histograms, IMR control charts, and both potential process capability indices (Cp, Pp) and actual capability indices (Cpk, Ppk) [76–77].

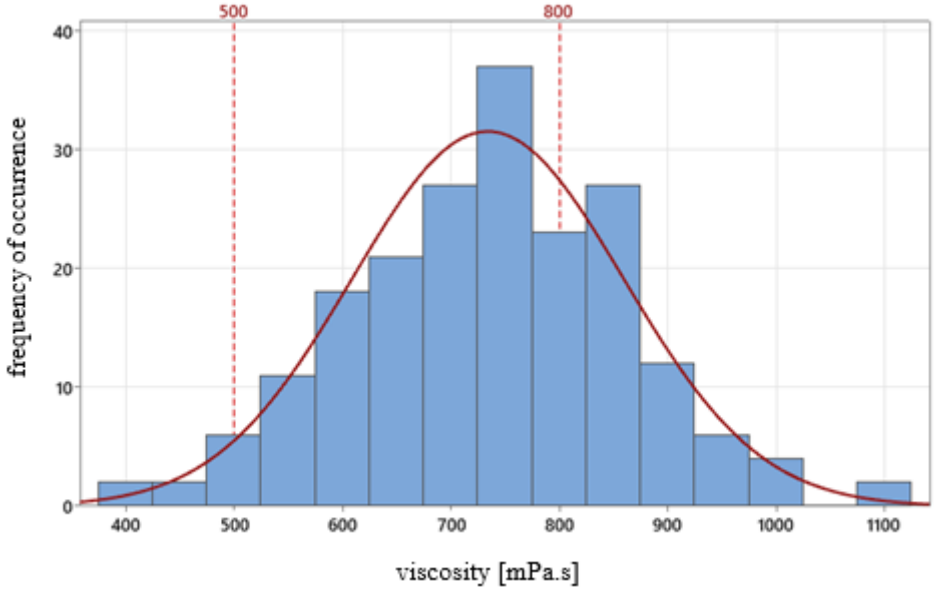


Figure 2. Distribution of Historical Data.
Source: Developed by the Author.

Figure 2 presents the historical data obtained. The dataset reflects the overall variability of the single-component paint production process, encompassing 198 batches produced between January 2021 and June 2023. The analysed values were recorded prior to the final adjustment stage, which involved either the addition of a solvent or the thickening of the base, depending on the initial viscosity parameter.

The dynamic viscosity values indicated by dashed lines (500 mPa·s and 800 mPa·s) represent the accepted product specification limits. A substantial proportion of observations fall outside these limits, indicating a high level of process variability. From the perspective of data compliance analysis, such deviations signal the necessity for further investigation into the sources of variability. From a quality management standpoint, the excessive dispersion of measurements increases the risk of non-compliance with requirements and reduces process stability.

Based on the distribution of process data, both a variability problem—resulting from the wide dispersion of results exceeding the expected distribution—and a location problem were identified. In order to understand the underlying cause-and-effect relationships and effectively reduce process instability, a thorough root cause analysis was required.

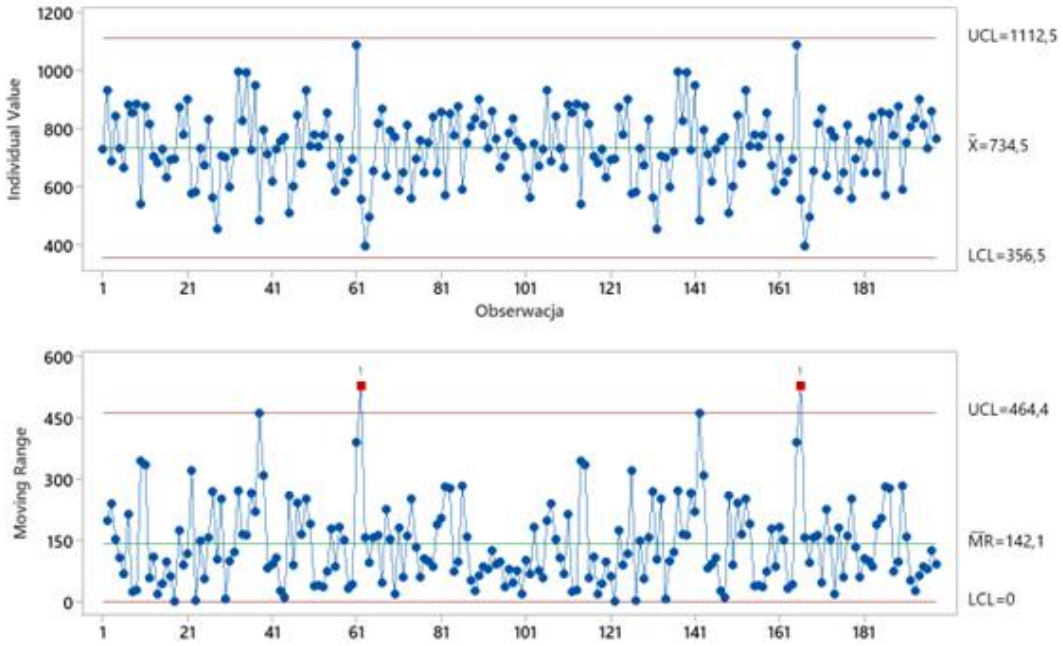


Figure 3. IMR Control Chart for the Analysed Process.
Source: Developed by the Author.

Figure 3 presents the distribution of results in relation to the control limits determined on the I and MR charts.

The control limits on the I chart were calculated using the equations (3) and (4) below.
First, the arithmetic mean of all measurements was calculated (1).
By substituting the values, the following was obtained:

$$\bar{I} = \frac{\sum_{i=1}^{n} I_i}{n} = \frac{731+931+\cdots+765}{198} = 734{,}5 \quad (1)$$

The average moving range value was calculated using equation (2).

$$\overline{MR} = \frac{\sum_{i=2}^{n}(X_i - X_{i-1})}{n-1} = \frac{200+242+\cdots+94}{197} = 142.1 \quad (2)$$

The obtained values made it possible to determine the upper and lower control limits UCL_I and LCL_I:

$$UCL_I = \bar{I} + 2.66 \cdot \overline{MR} = 734.5 + 2.66 \cdot 142.1 = 1112.5 \quad (3)$$

$$LCL_I = 734.5 - 2.66 \cdot 142.1 = 356.5 \quad (4)$$

When analyzing the I chart, it should be noted that all points fell within the limits defined by the upper (UCL_I) and lower (LCL_I), control limits, which indicated the presence of short-term variation exceeding long-term variation. From the perspective of further optimization actions, it was necessary to take steps aimed at identifying the root causes of short-term variation.

The control limits on the I chart showed the actual extent of process variation, ranging from 356.5 mPa·s to 1112.5 mPa·s—significantly exceeding the established specification limits of 500–800 mPa·s. In terms of quality, such a large spread of results beyond the specified boundaries meant producing products that failed to meet requirements. To ensure lasting compliance with the targeted viscosity parameters, optimization measures were needed.

The control limits for the MR chart were determined using equations (5) and (6). To calculate the average moving range $\overline{MR}$, equation (2) was applied. Substituting the values yielded:

$$UCL_{MR} = \overline{MR} \cdot D_4 = 142.1 \cdot 3.267 = 464.2 \quad (5)$$

$$LCL_{MR} = \overline{MR} \cdot D_3 = 142.1 \cdot 0 = 0 \quad (6)$$

The difference between the estimated value of UCL_{MR} and the result obtained from the Minitab software was due to rounding assumptions. However, this did not affect the interpretation of process data in the analysed case study.

Analysis of the values obtained from the MR chart indicated that two points exceeded the upper control limit, confirming the occurrence of special cause variation [71].
It should be emphasised that when calculating UCL_{MR} on the moving range chart, the constant D_4 is equal to 3.267, while the constant D_3 equals 0.

In summary, in the analyzed case of 198 measurements, the process exhibited both location and variation problems. The presence of special cause variation usually prompts immediate corrective actions; however, due to the process shift and the wide distribution, the priority in this case was to understand the cause-and-effect chain.

4.2. Measurement System Analysis

Recognising dynamic viscosity as the key parameter in the qualitative assessment of the analyzed process, it was necessary to develop a uniform standard for the measurement

procedure. The tests were carried out using a Brookfield DV-E viscometer. Before starting each test, the samples were thermostated to a temperature of 23 °C ± 0.5°C. The dynamic viscosity measurement was performed using spindles sp3 or sp4, depending on the value of the measured parameter, which affected the spring load. The procedure was conducted for deflection in the range of 20% to 80%. If the values obtained for spindle sp3 were outside the required range, they were replaced with spindle sp4. The tests were carried out directly in 1-liter cans. Viscosity results were recorded 30 seconds after starting the stopwatch and stabilizing the device readings.

The measurement system analysis in the described case study was performed based on the matrix shown in Figure 4.

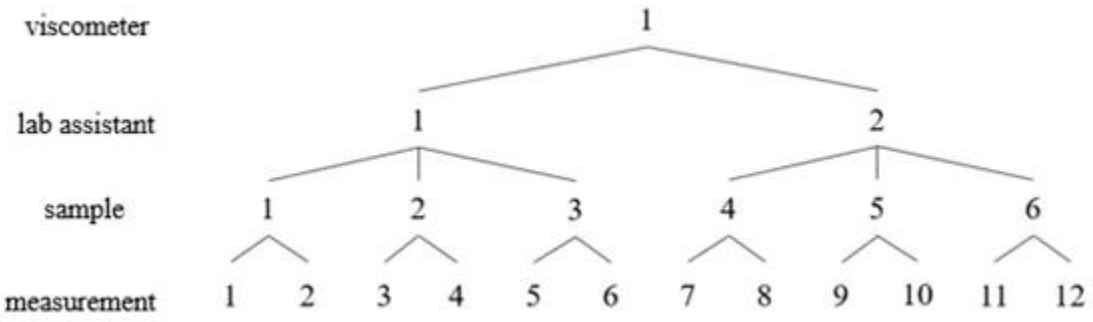


Figure 4. Sampling Tree Structure – Measurement System Analysis.
Source: Developed by the Author.

A single measuring device was used for the study. The experiment involved two laboratory technicians, each testing the same three samples.

Each sample was measured twice, with the second measurement series conducted on the following day. The samples were coded with assigned numbers, and the technicians were unaware of the coding system to ensure objectivity.

To comprehensively determine the characteristics of the measurement system, Xbar-R control charts were used. Based on the data collected during sampling, the relevant charts were generated and are presented in Figure 5.

Figure 6 illustrates the Xbar-R control chart broken down by individual technicians participating in the study, allowing identification of potential shifts or lack of interchangeability. In the evaluated case, the shift value was marginal, indicating that the technicians were fully interchangeable.

Analysis of the R chart revealed no special causes within the test, confirming that the measurement-to-measurement variation was consistent, predictable, and stable, and therefore there were no grounds to question the obtained results.

In turn, interpretation of the Xbar chart demonstrated that the measurement system functioned correctly. All points exceeded the established control limits, indicating that measurement-to-measurement variation was not the primary source of variability in the analysed test.

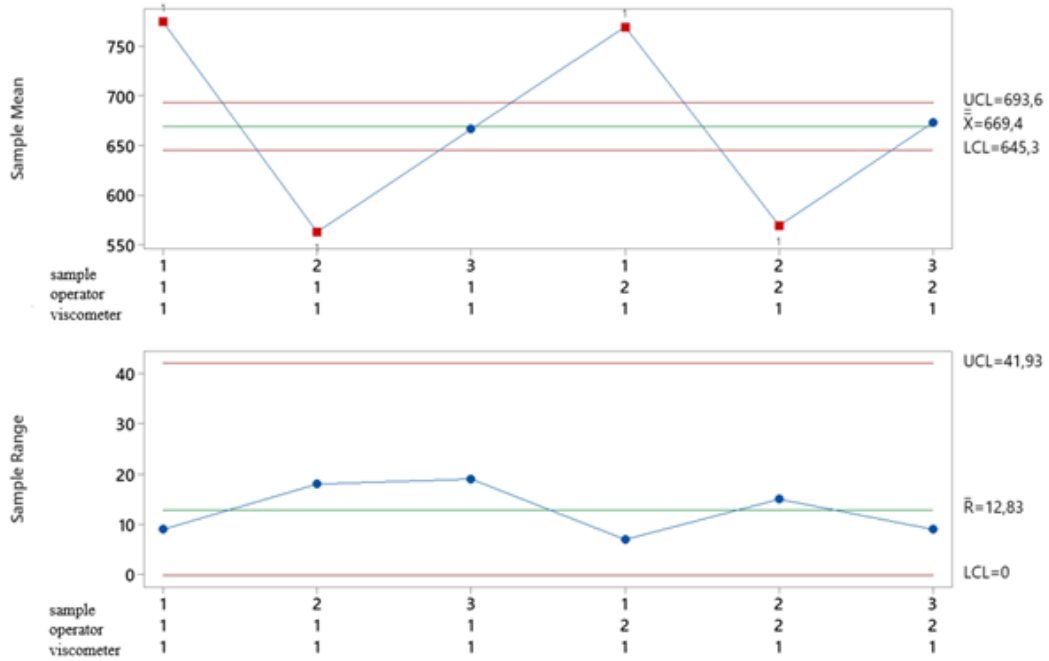


Figure 5. Xbar-R Control Chart – Measurement System Analysis.
Source: Developed by the Author.

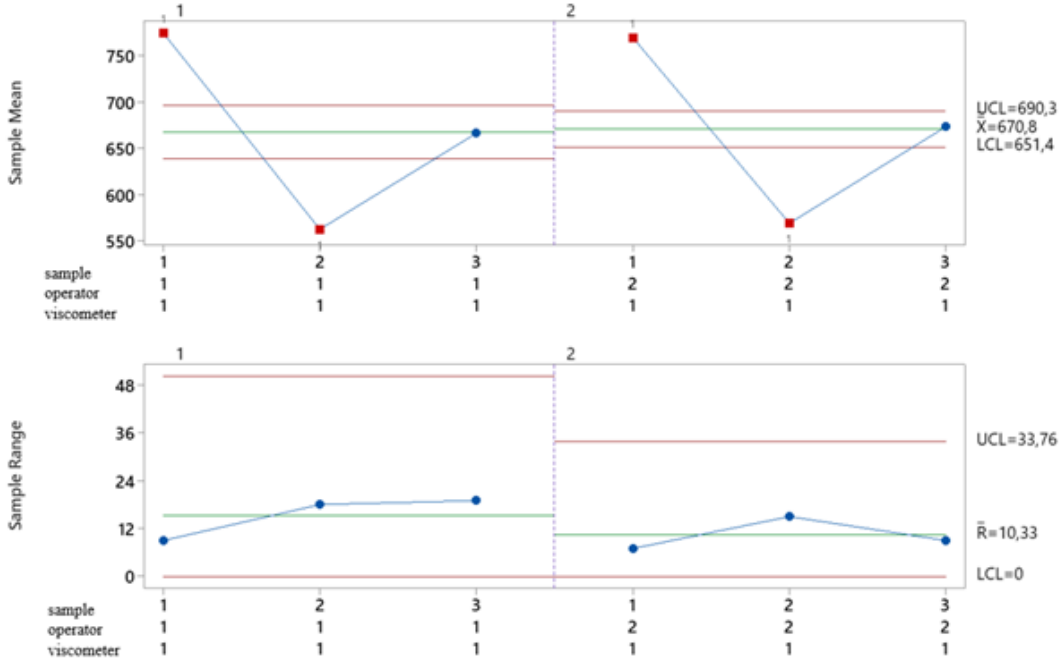


Figure 6. Xbar-R Control Chart – Measurement System Analysis by Operator.
Source: Developed by the Author.

Based on the R chart, it was also possible to determine whether the measurement system had a sufficient level of resolution. The analysis showed that the obtained values did not align at a single level but instead assumed a stepped pattern, which confirmed that the measurement unit value was sufficient to distinguish variability. From a quality requirements perspective, appropriate measurement system resolution allows for the detection of even minor changes in the process, which translates into more accurate deviation analysis. As a result, it becomes possible to monitor parameters more effectively and implement adequate actions, leading to greater stability and predictability of manufactured products [78].
The control limits on the Xbar chart were calculated using equations (9) and (10). First, it was necessary to compute the arithmetic mean of the mean values for each subgroup using equation (7), and then determine the mean range using equation (8). By substituting the obtained results into the formulas, the following values were derived:

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{n} \bar{x}_i}{n} = \frac{774.5+563+\cdots+673.5}{6} = 669.4 \quad (7)$$

$$\bar{R} = \frac{\sum_{i=1}^{k} R_i}{k} = \frac{9+18+\cdots+9}{6} = 12.83 \quad (8)$$

$$UCL_{Xbar} = \bar{\bar{x}} + A_2 \cdot \bar{R} = 669.4 + 1.880 \cdot 12.83 = 693.5 \quad (9)$$

$$LCL_{Xbar} = \bar{\bar{x}} - A_2 \cdot \bar{R} = 669.4 - 1.880 \cdot 12.83 = 645.3 \quad (10)$$

The control limits on the R chart were calculated using equations (11) and (12).

$$UCL_R = D_4 \cdot \bar{R} = 3.267 \cdot 12.83 = 41.92 \quad (11)$$

Due to the fact that the size of the analyzed subgroup was 2, the LCL_R assumed the value of 0.

$$n < 7, LCL_R = 0 \quad (12)$$

The values of the constants A_2, D_3 and D_4 depended on the number of observations in the subgroup.

Differences between the estimated control chart values and the results obtained from the Minitab software were due to rounding and did not affect the interpretation of process data in the analyzed case study.

Based on the values from the Xbar chart, it was possible to estimate the precision of the measurement system (Figure 5). The total number of points was 6, of which 4 exceeded the control limits, representing approximately 66.6%. For the measurement system to be considered

precise, with n = 2, more than 50% of the measurements should lie outside the limits. Table 1 illustrates the minimum number of points exceeding the control limits depending on the subgroup size.

Table 1. Minimum Number of Points outside the Control Limits in Relation to Subgroup Size.

Subgroup size n	Minimum number of points outside the control limits
2	50%
3	60%
4-6	70%
7-13	80%
14-50	90%
>50	100%

Source: Developed by the Author.

High repeatability of the measurement system enables consistent and reliable monitoring of key parameters in the process, which significantly strengthens the accuracy of quality assessments. As a result, corrective and improvement actions can be based on reliable data, ensuring control over the stability and compliance of manufactured products with the adopted requirements [73].

The results obtained in the analysis did not provide grounds to consider the measurement system inadequate; therefore, further examination of the process was possible.

4.3. Identyfication of Process Variability – Driving Areas

The next significant stage within the framework of the statistical process control model and experimental design, incorporating the Pareto principle, is the identification of dominant areas affecting variability, enabling a better understanding of cause-and-effect relationships in the studied process.

In the analysed case, three variability areas were distinguished – sample-to-sample, batch-to-batch, and operator-to-operator. To capture variability accurately, data collection began on Monday (batches 1 and 6), continued through Wednesday (batches 2 and 7), Friday (batches 3 and 8), the following Monday (batches 4 and 9), and ended on the next Friday (batches 5 and 10). Based on process knowledge, the selected days were considered significant due to potential misalignment after the weekend or immediately before it, as well as due to deliveries of different raw material batches. The sampling tree is shown in Figure 7.

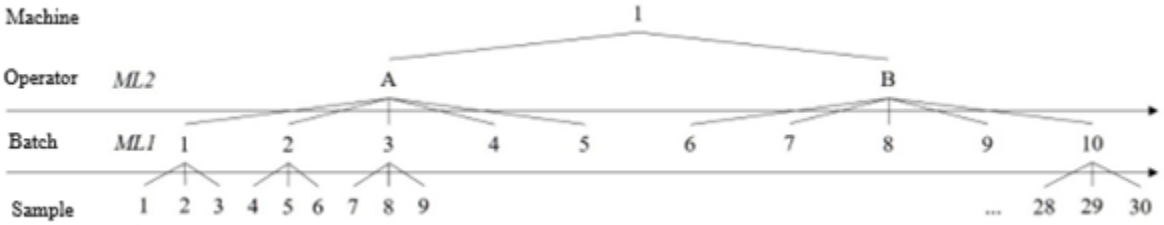


Figure 7. Sampling Tree.
Source: Developed by the Author.

For simplicity in analyzing the sampling tree, two division lines—ML1 and ML2—were introduced, separating individual areas of variability. Based on Figure 8, a table of sources of variability (Table 2) was prepared, systematising the process parameters that could be influenced (x) as well as the disturbing factors (z).

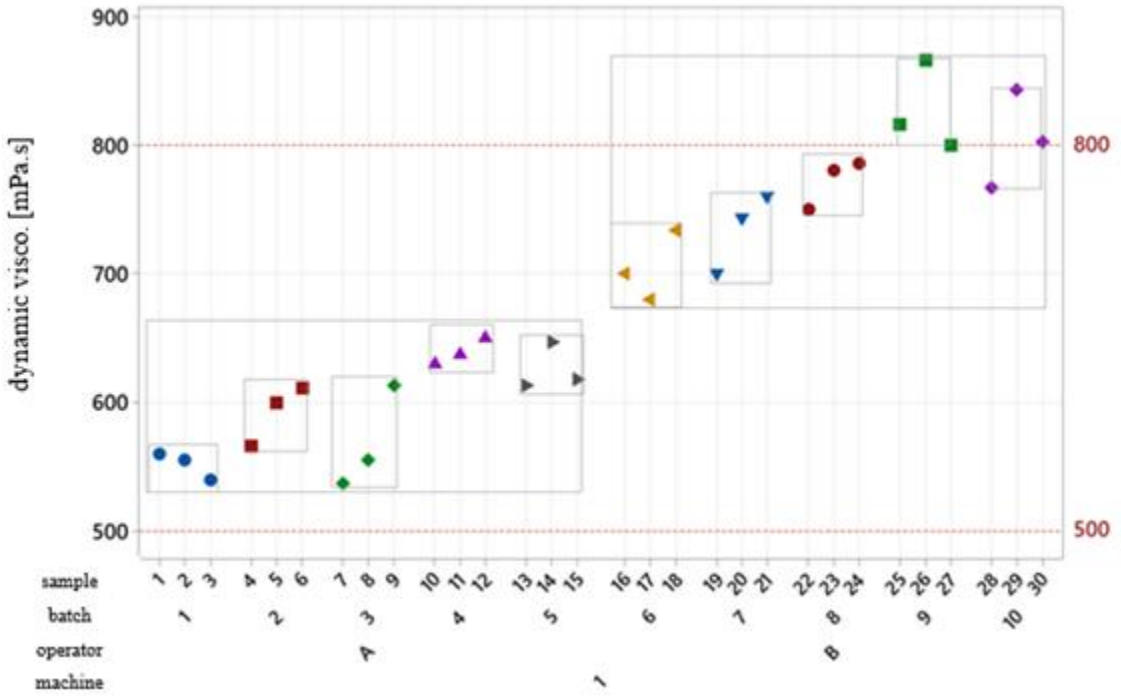


Figure 8. Practical Analysis – Box Plot.
Source: Developed by the Author.

The practical method is a primary approach within the interpretation of results, involving the presentation of measured values in alignment with the adopted data collection scheme, which allows for the immediate identification of the dominant area – Figure 8.

The obtained values indicated that the actual variability of the process had been captured — measurements ranged from 537 to 866 mPa·s, confirming the correct preparation of the sampling tree. Furthermore, no special causes were observed, as the absence of outlier measurement points within individual batches indicated the presence of only natural variability. No distinct trends were observed either, and the individual measurements presented in the rectangles representing the batches were arranged randomly. The obtained results formed the basis for conducting further in-depth studies aimed at minimising variability in terms of the adopted quality requirements.

Based on the chart, it could be concluded that the greatest impact on variability was associated with the differences between individual operators—the rectangles representing data from operator A and operator B did not overlap. In contrast, the effect of variability between batches,

as well as within individual samples, was clearly smaller and less significant in the context of the overall natural process variability.

Table 2. Table of Sources of Variability.

Area of variability	Factors contributing to variability
Operator-to-operator	– Engagement of the operator – precision and diligence in performing procedures; – Experience of the operator – knowledge of processes, recipes, and ability to react quickly to deviations; – Execution of the dispensing nozzle cleaning procedure; – Type of dissolver used (tank with cooling or without cooling); – Precision in dosing input raw materials; – Dosing speed; – Immersion depth of the dissolver disc; – Rotational speed of the dissolver disc; – Precision of pump settings; – Preparation of the mixer before the process (e.g., setting input parameters); – Process temperature – monitoring and maintaining proper thermal conditions; – Adherence to technological times – compliance with set timeframes.
Batch-to-batch	– Quality of input raw materials; – Selection of the appropriate type of resin from the control panel (epoxy, polyurethane, alkyd); – Choice of the proper solvent (e.g., D40, White Spirit, Xylene); – Type of thickener (e.g., polyamide wax, bentonite); – Quality of thickener; – Ambient temperature; – Type of pigments (organic, inorganic); – Quality of pigments; – Type of defoaming additives (e.g., silicone-based, siloxane-based); – Quality of defoaming additives; – Type of flow-control additives (silicone-based, siloxane-based); – Quality of leveling-improving additives; – Type of filler (e.g. $CaCO_3$, $BaSO_4$); – Quality of fillers.
Sample-to-sample	– Degree of sample homogeneity; – Localized overheating of the sample; – Degree of thickener activation; – Sample temperature; – Level of contamination of the sampling tool

Source: Developed by the Author.

4.4. Design of Experiments

Based on the previous analyses, it was determined that, with respect to the dynamic viscosity parameter of the finished product, the most significant impact was the difference in how individual operators performed their tasks.

Referring to Table 2, which presents the identified areas of variability, factors potentially influencing the observed deviations were selected.

Process knowledge made it possible to distinguish key aspects and potential disturbances that could directly determine the differences associated with the work of different operators. In the first phase, the focus was on the thickener, which is responsible for shaping the product's rheology.

The following factors were selected for the experiment:

A: thickener – two approved suppliers;
B: thickener dosing method – speed;
C: maximum temperature during thickener dissolution;
D: relaxation time of the thickener at a specified temperature after dissolution to improve activation;
E: disperser disc rotational speed.

Due to the chemical nature of the tested component, the recommended activation temperature—at which the raw material reaches maximum effectiveness—was in the range of 55–65°C, while the optimal relaxation time was 30 minutes.

As part of the planned activities, a fractional factorial experiment 2_V^{5-1} was applied [79]. The factors were tested at two levels (+ and −), in accordance with Table 3. Resolution V allows for separate analysis of main effects and two-factor interactions, which results in more accurate outcomes. It should be noted that the main effect is confounded with the fourth-order interaction (A = BCDE), and second-order interactions are associated with third-order interactions (AB = CDE).

Table 3. Table of Factors and Levels – DoE.

Factor	Level	
	-	+
A: supplier	X	Y
B: method of introducing the thickener into the system	portions	all
C: temperature [°C]	50	60
D: retention time [min]	0	30
E: rotational speed of the dispersing disc [rpm]	1000	2000

Source: Developed by the Author.

The first stage of the DoE tests was carried out on 2.5-liter samples prepared in the laboratory. The following constraints were applied in the experiment:

- Samples were prepared using one type of dissolver.
- The experiment involved one operator and one laboratory technician performing the measurements.
- Constant batches of thickeners were used: raw material x came exclusively from batch 1, while raw material y came from batch 2.
- The retention time of the thickener at the set temperature was measured from the moment the required temperature value was reached, after which the dispersing disc was immediately turned off.
- During thickener dosing, the dissolver operated at the speed set in the experimental matrix.
- The process was carried out in a 2.5-liter metal bucket, with the recipe recalculated for 2 liters.
- The diameter of the dispersing disc was 10 cm.

The fractional factorial experiment 2_V^{5-1} assumes 16 runs. To minimize the impact of potential disturbances, a replication strategy was applied, providing for each run to be performed twice. This made it possible to confirm the correctness of the obtained results. The tests were carried out in the laboratory, which allowed the adopted strategy to be implemented without excessive strain on resources.

No significant differences were found in the values for the individual combinations, confirming the repeatability of the dynamic viscosity results.

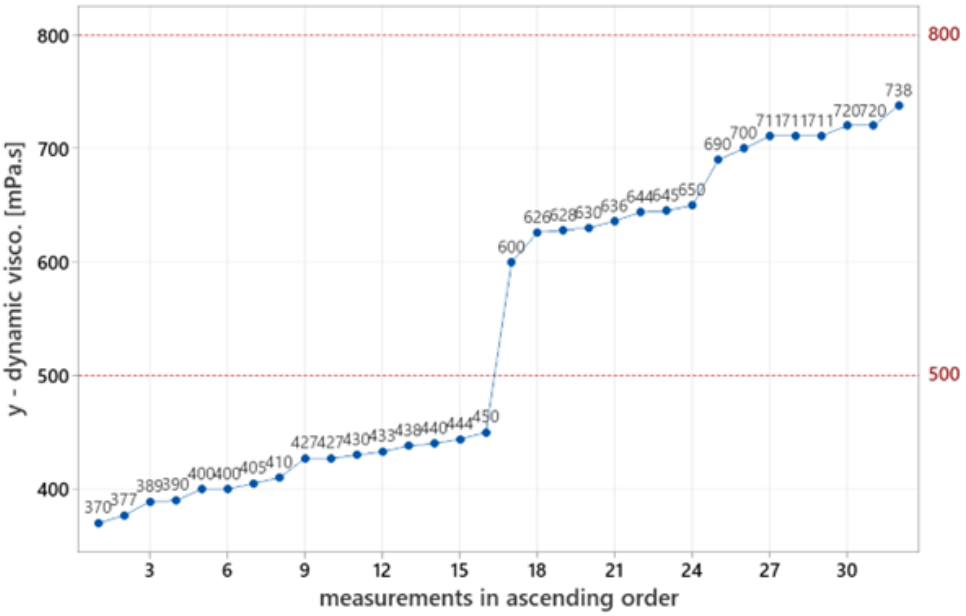


Figure 9. Time Series Plot.
Source: Developed by the Author.

The first stage of the analysis was to prepare a time series plot to examine whether there was noticeable variability in the obtained results. A time series plot makes it possible to assess the

representativeness of the results in the context of the phenomenon under study, which is the basis for drawing conclusions. The data on the chart were arranged in ascending order, from the lowest to the highest values, as shown in Figure 9.

A significant increase in dynamic viscosity from 450 mPa·s to 600 mPa·s between measurements 16 and 17 indicated a strong main effect in the examined system. The sudden change in value was the result of the reaction of one of the factors or interactions on the system, which was determined in subsequent tests as part of the conducted analysis. The experiment yielded results below the set limit, well-fitted measurements, and values from the upper range of the specification, confirming the correct selection of factors and their levels.

The next step in the research procedure was to prepare a scatter plot. This tool confirms the randomness of the experiment's sequence and rules out any dependency of the DoE results on time [80].

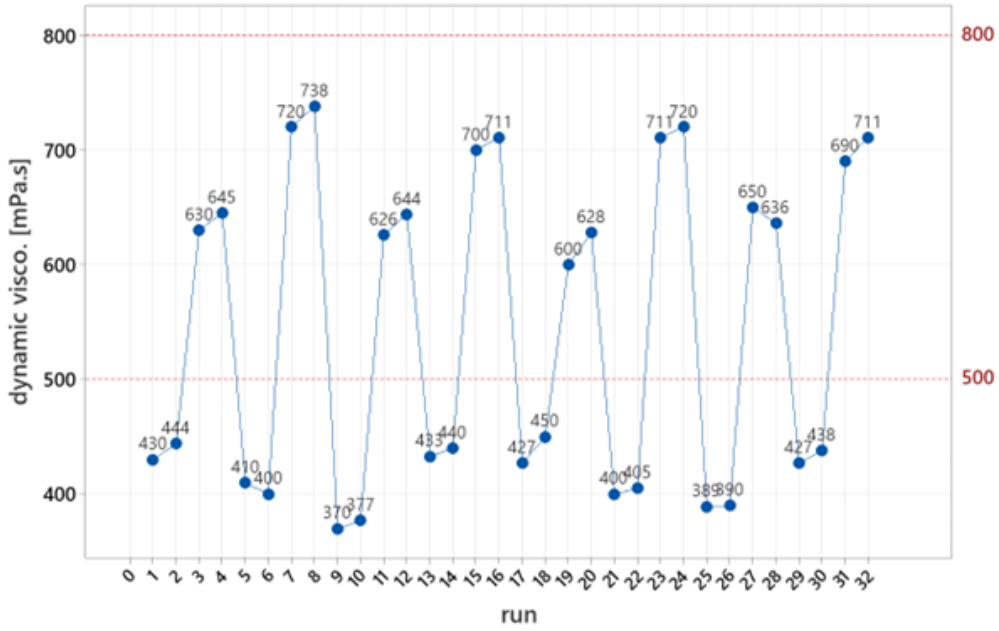


Figure 10. Scatter plot.
Source: Developed by the Author.

Figure 10 presents the actual order of the experimental runs. The scatter plot showed complete randomness, which proved that the obtained values were not time-dependent. No trends—such as a systematic increase or decrease—were observed, while the values themselves displayed an irregular pattern. An increasing or decreasing arrangement would indicate the presence of an external factor affecting the experiment and undermining the reliability of the analysis, which would necessitate repeating the experiments to obtain high-quality data.

Further data analysis focused on developing the standardized effects plot, which makes it possible to identify the dominant factors and significant interactions. The obtained results indicated that factor D played the dominant role (Figure 11).

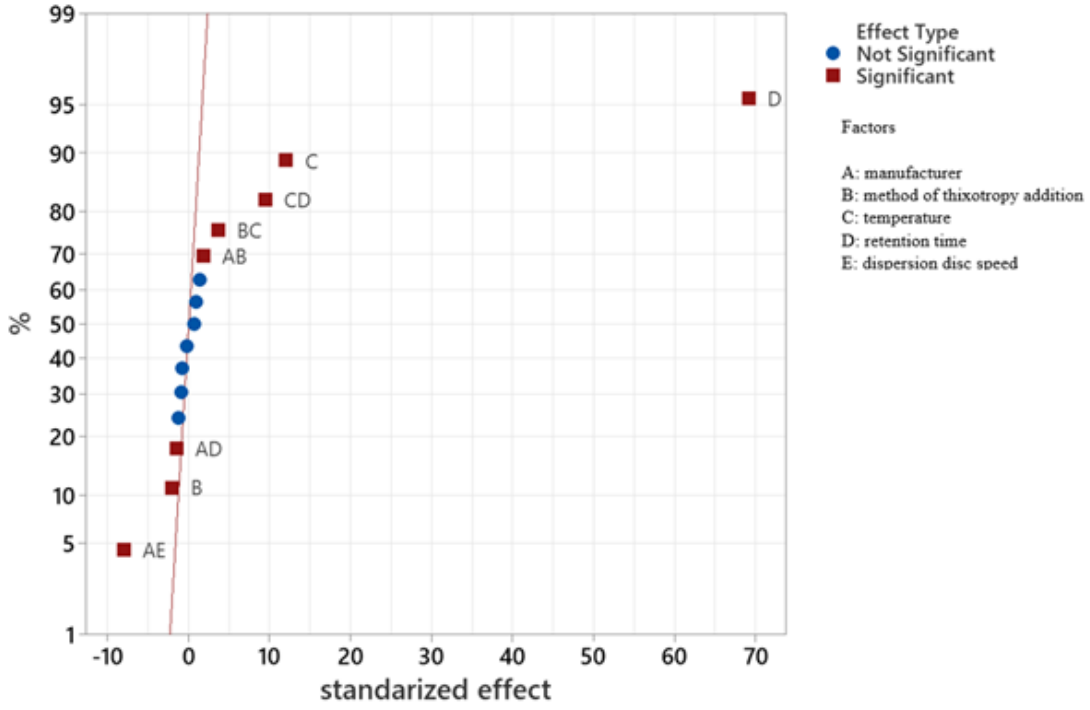


Figure 11. Standardized Effects Plot.
Source: Developed by the Author.

In addition to the significant impact of holding time, the importance of factors B and C, as well as the interactions CD, BC, AB, AD, and AE, was also identified. However, these exhibited lower significance, and the scope of their control depended on the effect values.

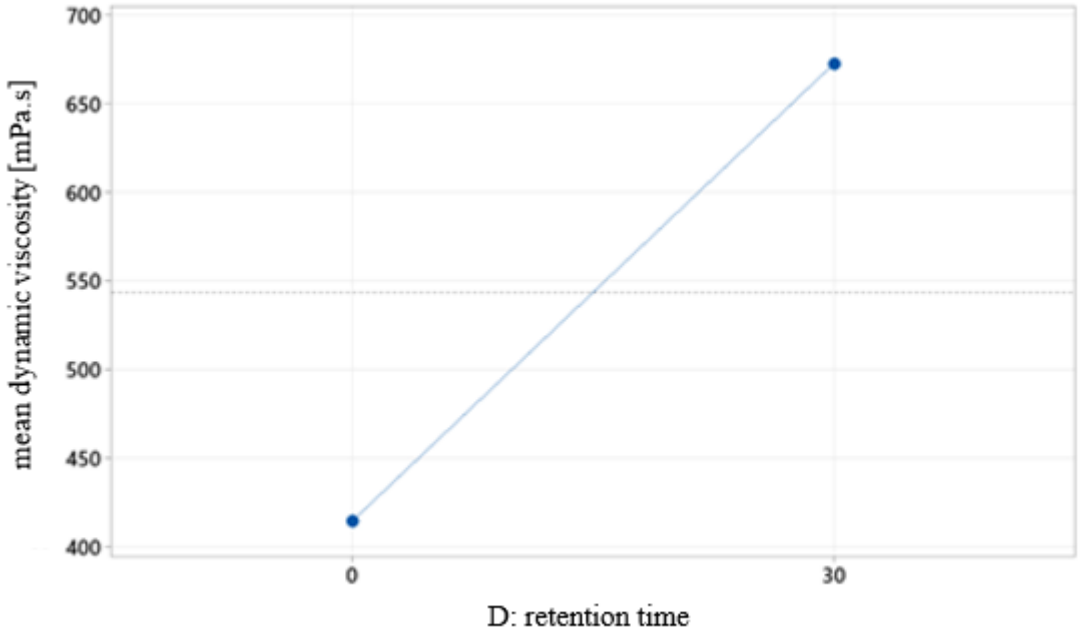


Figure 12. Main Effect Plot for D: Retention Time.
Source: Developed by the Author.

Higher effect values indicated a greater influence of a given factor or interaction, which made it possible to effectively target actions in process quality management. The chart was prepared assuming a statistical significance level of α = 20%, which was consistent with the Pareto principle and allowed the identification of the effects with the greatest impact on the analyzed process.

Due to the significant influence of retention time (factor D) on product quality, a main effects plot was developed to illustrate how changing the level of this factor from "−" (0 minutes) to "+" (30 minutes) affected the values of dynamic viscosity (Figure 12).

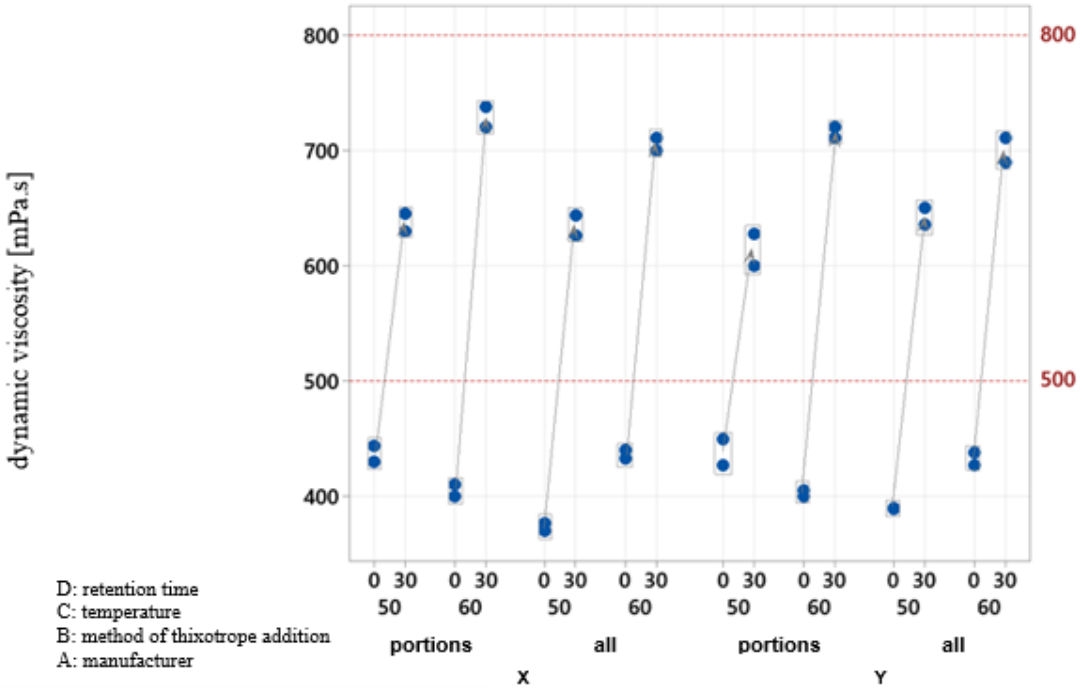


Figure 13. Box Plot – Effect of Factors on Dynamic Viscosity Parameter Value.
Source: Developed by the Author.

Interpretation of the chart showed that increasing the retention time from 0 to 30 minutes resulted in an increase in the average dynamic viscosity from 414.4 mPa·s to 672.5 mPa·s.

To fully understand the dependencies in the analyzed case, a box plot was used to present the factors shaping the natural variability of the process (Figure 13). Due to the negligible effect value of factor E (close to 0), its influence on viscosity was considered insignificant.

Analysing the data presented in Figure 13, it was observed that a significant portion of the measurements exceeded the defined specification limits. A particularly clear trend was noted in cases where the retention time was 0. At the same time, for samples within the accepted limits, a relationship was identified indicating that higher parameter values were achieved with longer retention time (factor D) and elevated temperature (factor C).

It was determined that achieving dynamic viscosity in the central range of specification limits was not dependent on the raw material suppliers nor on the method of thickener implementation.

However, the key factors proved to be maintaining a temperature of 50 °C and a retention time of 30 minutes.

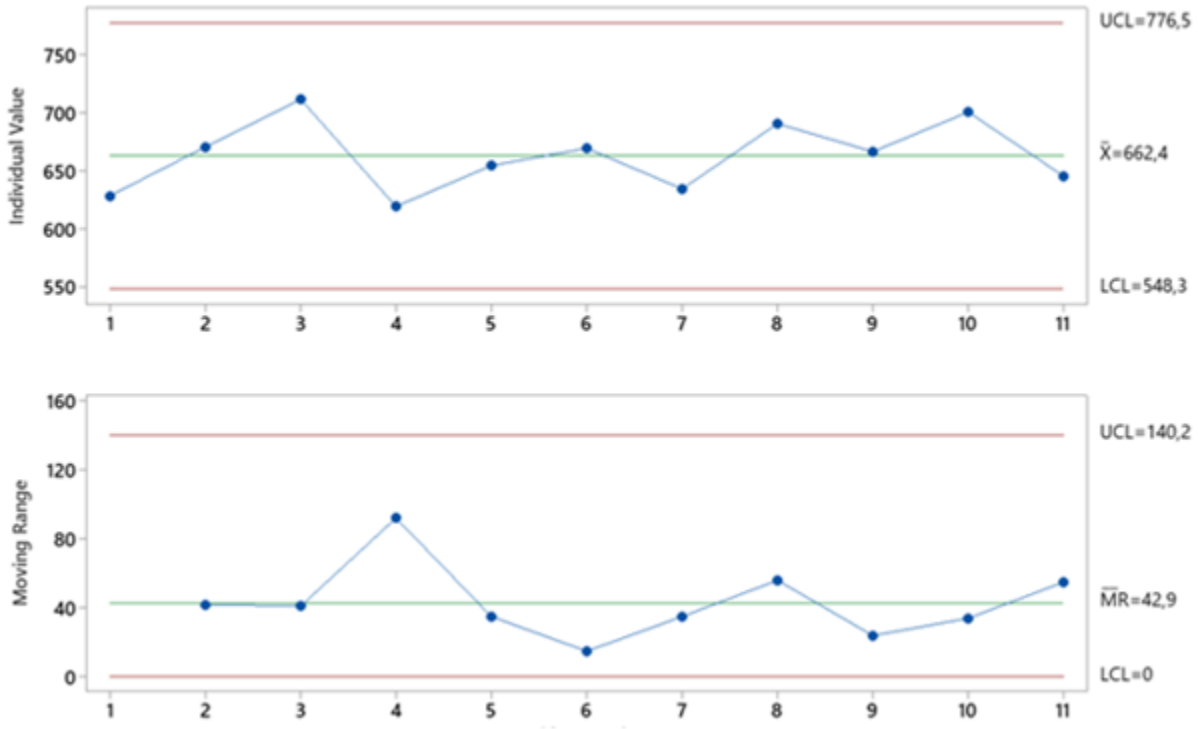


Figure 14. IMR Control Chart – Variability of Pilot Batches.
Source: Developed by the Authors.

These recommendations were introduced into the production environment to confirm their effectiveness under actual manufacturing conditions, rather than only in a laboratory scale. Figure 14 presents the IMR control chart illustrating the effect of process guidelines — retention time (30 minutes) and temperature (50°C) — on the obtained values. No other process areas were modified, as they were not part of the conducted experiment. The data relates to eleven pilot production batches.

The analysis of the individual value control chart indicated that the obtained dynamic viscosity measurements were within the range of 619–711 mPa·s, which was consistent with the established specification limits. The variability after implementing the recommended conditions was lower than for the data shown in Figure 3. However, it should be emphasized that further process monitoring is essential.

5. Discussion

The integration of Statistical Process Control and Design of Experiments within dynamic production environments represents an adaptive framework that enables the simultaneous management of variability and the identification of optimal process parameters. The inherently dynamic nature of production processes necessitates the application of flexible methodologies that support continuous monitoring and adjustment, ensuring that quality management systems can effectively respond to fluctuations in process performance and product quality.

Production flexibility plays a central role in such environments, allowing organisations to adapt to changing operational conditions. As highlighted by Torres et al., environmental dynamism promotes the exploration of new knowledge required to sustain competitiveness. In this context, the integration of SPC and DoE may be regarded as a strategic mechanism for enhancing production flexibility [81].

A holistic perspective is further reinforced by integrating SPC with maintenance strategies. Yin et al. demonstrate that combining statistical process monitoring with maintenance—particularly through delayed monitoring approaches—enables organisations to simultaneously address process quality and equipment reliability. Such integration improves system robustness and facilitates coordination across organisational units, ultimately increasing operational efficiency and reducing costs [82].

In addition to the Pareto principle, alternative optimisation concepts, such as the golden ratio ($\Phi \approx 1.618$), may also support process design [83]. While the Pareto principle focuses on identifying critical factors, the golden ratio can contribute to maintaining balance between efficiency and variability reduction. In manufacturing contexts, this principle may support the development of stable yet flexible processes, particularly in relation to sustainable resource management and environmental considerations.

The integration of SPC and DoE also aligns with the growing emphasis on sustainability. Manufacturers increasingly seek to minimise waste and optimise resource utilisation, including reductions in energy consumption and material losses. This perspective is consistent with broader industrial trends, where efficiency and environmental responsibility are treated as equally important objectives [84–85].

Furthermore, the proposed model is consistent with condition-based maintenance strategies. Du et al. show that the use of SPC charts for monitoring equipment condition enables real-time, data-driven maintenance decisions, thereby reducing downtime and improving reliability.This complements the experimental capabilities of DoE, allowing organisations to optimise both quality and operational performance within a unified framework [86].

The importance of organisational capabilities, particularly absorptive capacity, is also evident. Patel et al. emphasise that organisations capable of simultaneously exploring new solutions and refining existing processes are better positioned to implement time-based manufacturing practices. This aligns with the SPC–DoE integration approach, which supports informed, data-driven decision-making [87].

The applicability of the integrated model is further confirmed across various industries. In the automotive sector, SPC–DoE integration supports compliance with ISO 9001 requirements and

contributes to reducing nonconformities and improving productivity [88]. Similarly, in the food industry, the combined application of SPC and DoE enables effective control of critical process parameters, ensuring compliance with safety and quality standards [89].

The incorporation of the Pareto principle strengthens the analytical framework by introducing a structured approach to prioritisation. Pareto charts facilitate the identification of the most influential factors, enabling organisations to focus on high-impact areas. This enhances decision-making processes and supports a culture of continuous improvement [49]. Moreover, integrating Pareto analysis with SPC improves the detection of critical variations and enhances responsiveness to process changes [60].

Similarly, within the DoE framework, the Pareto principle supports the identification of key variables influencing outcomes. Prioritising critical factors allows for more efficient experimental design, reducing complexity while maintaining effectiveness [61]. Consequently, the combined application of SPC, DoE, and the Pareto principle provides a comprehensive and synergistic approach to process optimisation.

The integration of these methods is also consistent with Lean Six Sigma principles. Lean focuses on waste reduction and process efficiency, whereas Six Sigma emphasises variability reduction and quality improvement. Their combined application results in a comprehensive strategy for enhancing operational performance and product quality.

6. Conclusions

The results of the study confirm that the proposed integrated model, combining SPC, DoE, and the Pareto principle, effectively supports the optimisation of quality management in production processes. The case study demonstrated that the simultaneous application of these approaches enables the identification of key factors influencing product quality and facilitates parameter optimisation aimed at reducing variability and improving process stability.

The findings support Hypothesis 1, confirming that the integration of the Pareto principle with SPC and DoE contributes to effective identification and control of the primary sources of variability, thereby enhancing quality management performance. The results indicate that this approach reduces the impact of undesirable process deviations and increases both stability and predictability.

The study also confirms Hypothesis 2, demonstrating that improvements in measurement system resolution, precision, and operator interchangeability significantly enhance the accuracy of decision-making in quality management. Reliable measurement systems are therefore essential for the correct identification of variability sources and the formulation of effective improvement actions.

Despite its advantages, the proposed model has several limitations. Its effectiveness depends on assumptions such as the normality of data distribution, while standard Shewhart control charts may have limited sensitivity to small or gradual process shifts. Additionally, the complexity of DoE increases with the number of analysed factors, and insufficient consideration of process knowledge may lead to incorrect conclusions. Organisational factors,

including data quality and a culture of continuous improvement, also play a crucial role in successful implementation.

Future research should focus on developing more universal analytical approaches, including methods that allow the application of control charts regardless of data distribution. Another important direction involves the development of tools capable of detecting both minor process shifts and significant deviations within a unified framework.

The integration of artificial intelligence and machine learning represents a promising avenue for further development. Adaptive systems capable of real-time learning and response could significantly enhance process optimisation and variability reduction, aligning with Industry 4.0 paradigms. Additionally, future studies should consider the cost-effectiveness of implementing the integrated model, particularly in small and medium-sized enterprises.

Further research should also incorporate sustainability considerations, including environmental impact assessment, carbon footprint reduction, and efficient resource management, as these factors increasingly influence long-term competitiveness [90].

Finally, the application of advanced modelling techniques, such as artificial neural networks and backpropagation algorithms, may support the prediction and control of external factors affecting quality systems. Such approaches could enhance system resilience, enabling organisations to maintain stability under changing operational conditions and achieve long-term performance and reliability.

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Conflicts of Interest: The author declares no conflict of interest.

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