Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AF07.20260213
Published: May 13, 2026

An Integrated Production Planning and Quality Control Framework for Job-Shop Manufacturing: A Case Study of a Precision Machining SME

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Abstract

Manufacturing organisations, particularly small and medium-sized enterprises, face challenges in coordinating production and maintaining consistent quality in job-shop environments characterised by high product variety and short life cycles. This study presents an integrated framework combining production planning, value stream mapping (VSM), multi-criteria decision-making (AHP), and statistical process control (SPC) to improve operational efficiency and process performance. A case study in a job-shop manufacturing system demonstrates how AHP prioritises production planning criteria and identifies the most suitable strategy, while VSM visualises material and information flow to highlight bottlenecks. SPC techniques, including control charts and process capability analysis, are applied to monitor and stabilise production processes, reducing variation and improving quality. Results indicate that the hybrid production planning system outperforms conventional push and pull strategies, and the systematic application of SPC reduces process variability, enhancing product consistency. The framework provides a structured, practical approach for small manufacturers to integrate planning and quality control, offering significant improvements in throughput, lead time, and product reliability. The study highlights the potential of combining relatively simple engineering tools in a systematic manner to achieve measurable performance gains in complex job-shop operations.

Keywords
Job-shop manufacturing, Production planning, Value Stream Mapping (VSM), Analytic Hierarchy Process (AHP), Statistical Process Control (SPC)

1. Introduction

Manufacturing organisations increasingly operate in highly competitive environments characterised by short product life cycles, high product variety, and pressure to improve operational efficiency (Slack, Chambers & Johnston, 2022; Panneerselvam, 2012). One of the most significant challenges in such environments is the effective coordination of production activities through efficient production planning and scheduling systems (Pinedo, 2016; Baker, 1974). Production planning determines how resources such as machines, labour, and materials are allocated in order to meet demand while minimising operational costs and delays (Slack, Chambers & Johnston, 2022). Effective scheduling is particularly important in job-shop manufacturing systems, where products follow different process routes and production volumes are relatively small (Jain & Meeran, 1999; Fanti, Palumbo & Settineri, 2019).

In job-shop production environments, each job typically consists of multiple operations that must be processed on specific machines in a predetermined sequence (Pinedo, 2016). Since machines can only process one job at a time and processing times differ between jobs, scheduling decisions must carefully balance machine utilisation, production lead time, and order completion deadlines (Baker, 1974; Panneerselvam, 2012). As a result, the job-shop scheduling problem is widely recognised as one of the most complex optimisation problems in operations research and industrial engineering (Jain & Meeran, 1999; Fanti, Palumbo & Settineri, 2019).

Traditional production planning systems relied heavily on tools such as Gantt charts (Gantt, 1910) and material requirements planning (MRP) systems to coordinate manufacturing activities (Slack, Chambers & Johnston, 2022). While these approaches remain widely used, modern manufacturing environments increasingly require more flexible and integrated planning systems capable of responding to variable demand and dynamic shop-floor conditions (Panneerselvam, 2012; Fanti, Palumbo & Settineri, 2019). The evolution of production planning systems has therefore progressed from basic scheduling techniques toward integrated systems combining advanced planning algorithms, decision-support methods, and real-time process monitoring (Pinedo, 2016; Buzacott & Shanthikumar, 1993).

In addition to production planning challenges, manufacturing firms must also ensure consistent product quality (Juran & Godfrey, 1999; Montgomery, 2020). Process variation can lead to defective products, increased rework, and reduced operational efficiency (Ross, 2016). To address these issues, statistical quality management techniques such as Statistical Process Control (SPC) are commonly applied to monitor process behaviour and detect abnormal variation during production (Wheeler & Chambers, 2010; Montgomery, 2020). SPC techniques enable organisations to maintain process stability and reduce variability by analysing measurement data using statistical tools such as control charts (Montgomery, 2020; Wheeler & Chambers, 2010).

Despite extensive research on production planning and quality control techniques, many small and medium-sized manufacturing enterprises still rely on informal scheduling practices and limited statistical monitoring (Slack, Chambers & Johnston, 2022; Panneerselvam, 2012). These limitations often result in inefficient production coordination and inconsistent product quality. Consequently, there is a growing need for integrated frameworks that combine production planning tools with statistical quality control methods in order to improve both operational efficiency and process performance (Montgomery, 2020; Rother & Shook, 2003).

This study addresses this need by developing and implementing an integrated framework combining production planning system design, value stream mapping, multi-criteria decision analysis, and statistical process control within a job-shop manufacturing environment (Rother & Shook, 2003; Saaty, 1980; Montgomery, 2020). The research aims to demonstrate how relatively simple engineering tools, when applied in a structured and systematic manner, can significantly improve production coordination and quality management in small manufacturing enterprises (Slack, Chambers & Johnston, 2022; Womack, Jones & Roos, 1990).

2. Literature Review

2.1 Production Planning and Scheduling in Manufacturing Systems

Production planning and scheduling are fundamental components of manufacturing system management (Pinedo, 2016; Baker, 1974). Effective planning ensures that resources are allocated efficiently, production schedules are coordinated, and customer demand is met within required time constraints (Slack, Chambers & Johnston, 2022). Early developments in production planning can be traced to the work of Taylor, Gantt, and Adamiecki, who introduced systematic approaches for organising industrial production activities (Taylor, 1911; Gantt, 1910; Adamiecki, 1913).

The complexity of modern manufacturing systems has led to the development of numerous production scheduling models and algorithms (Jain & Meeran, 1999; Pinedo, 2016). Job-shop scheduling problems have been widely studied due to their practical relevance in industries where products follow different processing routes (Baker, 1974; Fanti, Palumbo & Settineri, 2019). These problems involve assigning jobs to machines while minimising performance measures such as makespan, lead time, or tardiness (Pinedo, 2016; Buzacott & Shanthikumar, 1993).

Recent research has also explored the integration of advanced decision-support systems and optimisation algorithms for solving complex scheduling problems (Fanti, Palumbo & Settineri, 2019; Panneerselvam, 2012). Techniques such as simulation modelling, reinforcement learning, and heuristic optimisation have been proposed to improve scheduling performance in complex manufacturing environments (Chen et al., 2000).

However, many studies focus primarily on algorithm development rather than practical implementation in real manufacturing environments. As a result, there remains a gap between theoretical scheduling models and the operational realities of small manufacturing enterprises (Slack, Chambers & Johnston, 2022; Panneerselvam, 2012).

2.2 Lean Manufacturing and Value Stream Mapping

Lean manufacturing principles have been widely adopted to improve production efficiency by eliminating waste and improving process flow (Womack, Jones & Roos, 1990; Liker, 2004). Lean production systems emphasise continuous improvement, waste reduction, and efficient resource utilisation (Rother & Shook, 2003).

One of the most widely used lean tools is Value Stream Mapping (VSM), shown in Figure 1, which provides a visual representation of the flow of materials and information through a production process (Rother & Shook, 2003). VSM enables organisations to identify bottlenecks, delays, and non-value-adding activities within the production system (Liker, 2004). By comparing current-state and future-state value stream maps, organisations can design improved production processes that reduce waste and improve operational performance (Rother & Shook, 2003).

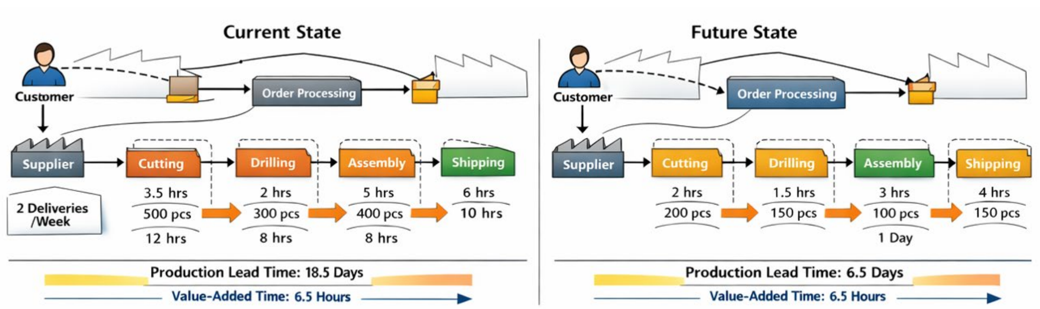

Figure 1. Current-State and Future-State Value Stream Maps of a Job-Shop Process

Value stream mapping is particularly useful in job-shop manufacturing environments, where complex routing and variable processing times often create inefficiencies in the flow of production activities (Pinedo, 2016; Womack, Jones & Roos, 1990).

2.3 Multi-Criteria Decision-Making in Production Planning

Selecting an appropriate production planning strategy often requires evaluating multiple competing criteria such as cost, flexibility, complexity, and responsiveness (Saaty, 1980; Ishizaka & Labib, 2011). Multi-criteria decision-making methods are therefore commonly used to support production planning decisions (Ishizaka & Labib, 2011).
One of the most widely used methods is the Analytic Hierarchy Process (AHP) (Figure 2), developed by Thomas Saaty in the 1970s (Saaty, 1980). AHP decomposes complex decision problems into hierarchical structures consisting of a decision goal, evaluation criteria, and alternative solutions. Pairwise comparisons between criteria are used to calculate priority weights, allowing decision-makers to determine the relative importance of each criterion and evaluate alternative strategies systematically (Saaty, 1980; Ishizaka & Labib, 2011).

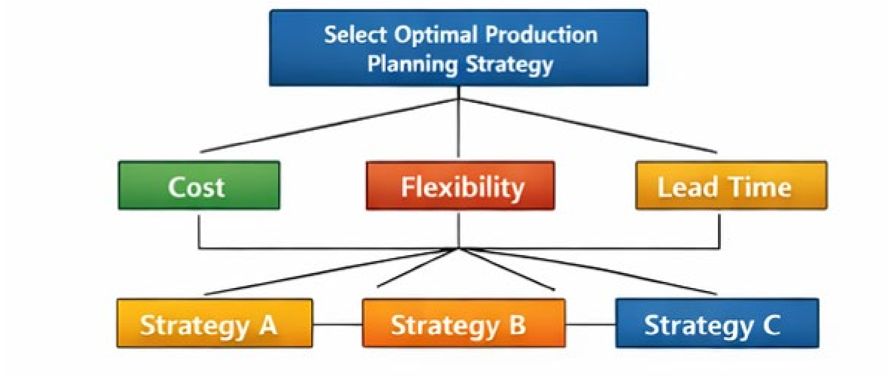

Figure 2. AHP Hierarchy for Production Planning Strategy Selection

AHP has been widely applied in manufacturing decision-making contexts, including supplier selection, technology evaluation, and production planning strategy selection (Panneerselvam, 2012; Slack, Chambers & Johnston, 2022).

2.4 Statistical Process Control and Process Capability

Statistical Process Control (SPC) is a widely used quality management technique that employs statistical methods to monitor and control manufacturing processes (Montgomery, 2020; Wheeler & Chambers, 2010). By analysing measurement data collected during production, SPC enables organisations to identify abnormal variations and maintain stable process conditions (Montgomery, 2020; Juran & Godfrey, 1999).

Control charts are the most common SPC tool used in manufacturing (Figure 3). These charts display process data over time and include statistical control limits that represent the expected range of variation for a stable process. Observations outside the control limits indicate the presence of special-cause variation requiring investigation (Montgomery, 2020; Wheeler & Chambers, 2010).

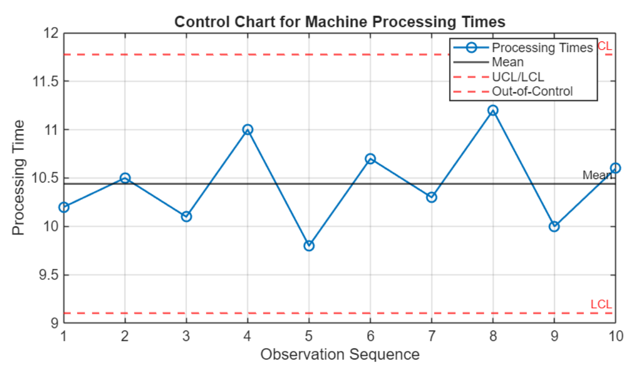

Figure 3. Control Chart for Machine Processing Times

In addition to monitoring process stability, process capability analysis evaluates whether a manufacturing process is capable of consistently producing parts within specified tolerance limits (Figure 4). Capability indices such as Cp and Cpk quantify the relationship between process variability and specification limits, providing valuable information for process improvement and quality management (Montgomery, 2020; Ross, 2016; Juran & Godfrey, 1999).

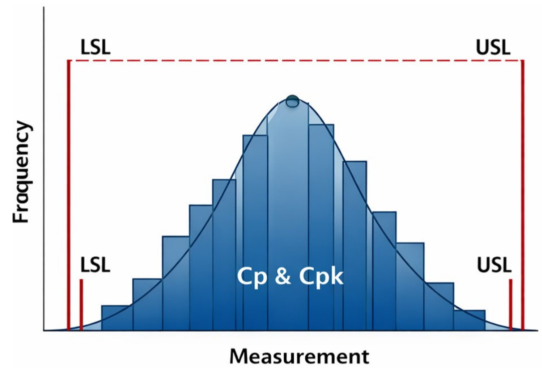

Figure 4. Capability Histogram Showing Process Distribution and Specification Limits

3. Methods

3.1 Research Approach

This study employed a case study research methodology to investigate the development and implementation of an integrated production planning and quality control framework within a small precision machining enterprise. Case study approaches are widely used in industrial engineering research when analysing complex operational systems within real industrial environments. The selected company operates as a job-shop manufacturing facility that produces precision-machined components for a range of clients. Job-shop environments are characterised by high product variety, irregular job arrivals, and complex routing requirements, which make production planning and quality management particularly challenging.

The research methodology was structured into four main stages. First, the existing production system was analysed using process observations and value stream mapping in order to identify operational inefficiencies. Second, an appropriate production planning strategy was selected using the Analytic Hierarchy Process (AHP), a multi-criteria decision-making method. Third, a structured production planning system was designed and implemented to improve scheduling and work-in-progress tracking. Finally, statistical process control techniques, including control charts, the PDCA improvement cycle, and process capability analysis, were implemented to monitor and improve the machining process. Data were collected through direct observation of production activities, dimensional measurements of machined components, and examination of company production records.

3.2 Production System Analysis Using Value Stream Mapping

The first stage of the research involved analysing the existing production system in order to identify inefficiencies in the flow of materials and information. This analysis was conducted through on-site observations of machining operations, discussions with company personnel, and documentation of production activities.

To systematically evaluate the production flow, Value Stream Mapping (VSM) was applied. Value Stream Mapping is a lean manufacturing technique used to visualise the sequence of activities required to produce a product and to identify sources of waste within the system. A current-state value stream map was developed to represent the flow of materials from raw material preparation through machining, inspection, and final delivery. The map documented the major process steps as well as key operational parameters such as cycle times, waiting times, and work-in-progress inventory levels.

The value stream analysis revealed several operational challenges, including irregular job scheduling, limited visibility of work-in-progress, and delays caused by insufficient coordination between machining operations. These findings highlighted the need for a structured production planning system capable of improving the coordination of production activities and reducing delays within the manufacturing process.

3.3 Selection of Production Planning Strategy Using the Analytic Hierarchy Process

Following the analysis of the existing production system, the next stage involved selecting an appropriate production planning strategy. In job-shop manufacturing environments, several planning approaches may be used, including push systems, pull systems, and hybrid systems that combine elements of both. To evaluate these alternatives systematically, the Analytic Hierarchy Process (AHP) was applied.

AHP is a structured multi-criteria decision-making method that decomposes complex decisions into a hierarchical framework consisting of a decision goal, evaluation criteria, and alternative solutions. In this study, the decision goal was to identify the most suitable production planning system for the company's operational environment.
Five evaluation criteria were identified based on the literature on production planning and consultation with company personnel:

- implementation cost
- operational flexibility
- system complexity
- data requirements
- suitability for job-shop manufacturing

Pairwise Comparison Matrix
The relative importance of the evaluation criteria was determined using pairwise comparisons as shown in Table 1. In this approach, each criterion is compared with every other criterion using the standard nine-point AHP importance scale. The results are organised in a pairwise comparison matrix, which represents the relative importance of each criterion with respect to the decision goal.

Table 1. Example Pairwise Comparison Matrix for Production Planning Criteria

Criteria	Cost	Flexibility	Complexity
Cost	1	1/3	2
Flexibility	3	1	4
Complexity	1/2	1/4	1

Priority Weights
The comparison matrix was normalised in order to calculate the priority weights of the evaluation criteria. These weights represent the relative contribution of each criterion to the final decision. In the context of job-shop manufacturing, operational flexibility and suitability for variable production environments were found to be the most influential factors. Table 2 shows that Flexibility is the most important factor for job-shop production.

Table 2. Normalized Weights for Production Planning Criteria

Criterion	Weight
Flexibility	0.45
Cost	0.30
Complexity	0.25

Ranking of Alternatives
The alternative production planning systems, push, pull, and hybrid approaches, were evaluated against the weighted criteria, shown in Table 3. Each alternative was assigned a score based on its performance relative to the evaluation criteria. The weighted scores were then aggregated to produce an overall ranking of the alternatives. The AHP analysis indicated that a hybrid production planning system provided the most appropriate balance between operational flexibility and implementation complexity. This system was therefore selected for implementation in the next stage of the research. According to Table 3, the hybrid production planning system is the most suitable.

Table 3. AHP Scores for Production Planning Alternatives

System	Score
Push	0.22
Pull	0.34
Hybrid	0.44

3.4 Design and Implementation of the Production Planning System
Based on the results of the AHP decision analysis, a structured production planning system was designed for the company. The objective of this system was to improve the coordination of machining activities, provide better visibility of work-in-progress, and enable more effective scheduling of production jobs.

The planning system was implemented using spreadsheet-based tools that recorded job information, machining sequences, and expected completion times. Production scheduling sheets were introduced to document the sequence of machining operations and to track the progress of each job through the production process. Work-in-progress tracking mechanisms were also implemented to provide a clear overview of the status of all active production orders. The design of the system emphasised simplicity and practicality in order to ensure that it could be easily used by company personnel. By centralising production information and improving the visibility of job progress, the planning system enabled management to identify production bottlenecks and allocate machining resources more effectively.

3.5 Statistical Process Control Using Control Charts
To monitor the performance of the machining process, Statistical Process Control (SPC) techniques were introduced. SPC uses statistical tools to monitor process behaviour and detect deviations from normal operating conditions.
Dimensional measurements of a critical machined feature were collected during production and organised into subgroups of equal size. The data were analysed using X-bar and R control charts, which are commonly used in manufacturing to monitor process stability.

The X-bar chart was used to track variations in the process mean, while the R chart was used to monitor variation within each subgroup. Control limits were calculated using standard control chart constants corresponding to the subgroup size. These limits represent the expected range of variation for a stable process.

By plotting the subgroup averages and ranges on the control charts, it was possible to determine whether the machining process was operating under statistical control or whether special-cause variations were present. The control charts, therefore, provided a systematic method for identifying abnormal process behaviour and initiating corrective action when necessary.

3.6 Continuous Improvement Using the PDCA Cycle
In addition to statistical monitoring, the study incorporated the Plan-Do-Check-Act (PDCA) cycle as a framework for continuous improvement. The PDCA cycle is widely used in quality management systems to guide systematic problem solving and process improvement.

In the planning stage, production data and process measurements were analysed to identify sources of variation and inefficiencies. During the implementation stage, improvements such as the production planning system and statistical monitoring tools were introduced. In the checking stage, control charts and process capability analysis were used to evaluate the effectiveness of the implemented changes. Finally, in the action stage, corrective measures were developed to address any remaining process deviations.

The PDCA cycle ensured that improvements to production planning and quality control were implemented in a structured and iterative manner.

3.7 Process Capability Analysis
After establishing statistical control of the machining process, a process capability analysis was performed to determine whether the process was capable of consistently meeting the specified dimensional tolerances. Process capability analysis evaluates the relationship between the natural variability of a process and the specification limits defined by the product design.

The process standard deviation was estimated from the average range of the subgroups using standard statistical relationships. The process capability index C_p and the centred capability index C_{pk} were then calculated.
The process capability index is defined as

$$C_p = \frac{USL - LSL}{6\sigma}$$

where $USL$and LSLrepresent the upper and lower specification limits and $\sigma$is the estimated process standard deviation.

The centred capability index is defined as

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

where μ represents the process mean. These indices provide a quantitative measure of the ability of the machining process to produce components within the required tolerance limits.

3.8 Integration of Production Planning and Quality Control

The final stage of the methodology involved integrating the production planning system with statistical quality monitoring tools. The combination of structured production scheduling, statistical process control, and continuous improvement methods created a coordinated production management framework.

This integrated approach enabled production managers to monitor job progress, track work-in-progress, analyse process variation, and implement corrective actions based on quantitative data. The framework, therefore, supports both improved production efficiency and enhanced product quality within the job-shop manufacturing environment.

5. Results and Discussion

4.1 Production System Analysis

The initial assessment of the production system revealed several operational inefficiencies typical of small job-shop manufacturing environments. Prior to the implementation of a structured planning system, production activities were largely coordinated informally. Job prioritisation was frequently based on immediate operational requirements rather than a systematic scheduling approach. As a result, production managers had limited visibility of work-in-progress (WIP), and machining operations were often interrupted by delays associated with incomplete job information or machine availability.

A current-state value stream map was constructed to document the flow of materials and information through the manufacturing process. The map included the primary production stages of material preparation, machining, inspection, and order completion. The analysis indicated that significant portions of the total production lead time consisted of waiting periods between machining operations. These delays were primarily caused by poor coordination between process stages and the absence of a structured scheduling mechanism.

The value stream analysis, therefore, confirmed that improvements in production planning and job tracking were required in order to reduce waiting times and improve overall production efficiency.

4.2 Selection of Production Planning Strategy

The selection of an appropriate production planning strategy was conducted using the Analytic Hierarchy Process (AHP). Three alternative planning approaches were evaluated: push production systems, pull production systems, and hybrid systems combining elements of both approaches.

The decision criteria included implementation cost, operational flexibility, system complexity, data requirements, and suitability for job-shop production environments. Pairwise comparisons of these criteria indicated that operational flexibility and suitability for variable production environments were the most influential factors in the decision process. This result is consistent with the characteristics of job-shop manufacturing systems, where production schedules must accommodate varying product types and unpredictable job arrivals.

The weighted evaluation of the alternative planning strategies demonstrated that a hybrid production planning system achieved the highest overall score. The hybrid approach combines structured scheduling with demand-driven adjustments, allowing production activities to remain flexible while still maintaining a degree of operational control. Based on this analysis, the hybrid planning strategy was selected for implementation in the company’s production system.

4.3 Implementation of the Production Planning System
Following the AHP decision analysis, a structured production planning system was introduced. The system was implemented using spreadsheet-based scheduling tools that recorded job information, machining sequences, and estimated completion times. The planning sheets allowed production jobs to be prioritised and monitored as they progressed through the machining stages.

The introduction of the planning system significantly improved the visibility of production activities. Management was able to monitor the status of active jobs and identify potential bottlenecks more effectively. The system also enabled better coordination between machining operations by ensuring that necessary job information was available before production began.

Operational observations following the implementation of the planning system indicated measurable improvements in production coordination. Waiting times between machining operations were reduced, and work-in-progress inventory became easier to monitor. These improvements contributed to shorter production lead times and more efficient use of machining resources.

4.4 Statistical Process Control Results
Statistical Process Control (SPC) techniques were introduced to monitor the performance of the machining process and identify sources of variation. Dimensional measurements of a critical machined feature were collected from multiple production batches and organised into subgroups for analysis.

The data were analysed using X-bar and R control charts, which were used to monitor variations in the process mean and subgroup variability. The control limits for the charts were calculated using standard statistical constants corresponding to the subgroup size.

The control chart analysis showed that the majority of observations fell within the calculated control limits, indicating that the machining process was generally operating under conditions of statistical control. This suggests that the observed variation in the process was largely attributable to common-cause variation inherent to the machining operation.

However, a small number of points on the range chart indicated increased variability in certain production batches. These variations may be associated with factors such as tool wear, machine adjustments, or changes in cutting conditions. The use of SPC therefore provided a systematic method for identifying potential disturbances in the machining process and enabled the company to respond proactively to abnormal conditions.

4.5 Process Capability Analysis
After establishing statistical control of the machining process, a process capability analysis was conducted to determine whether the process was capable of consistently meeting the required dimensional tolerances. The process standard deviation was estimated from the average range of the measurement subgroups using the appropriate statistical constants.

Using the estimated process variability, the process capability indices C_p and C_{pk} were calculated. These indices evaluate the relationship between the natural variability of the machining process and the specification limits defined for the component. The capability analysis indicated that the process variability was relatively well controlled and that the machining process had the potential to meet the required tolerance limits. However, the difference between the C_p and C_{pk} values suggested that the process mean was not perfectly centred between the specification limits. This indicates that small adjustments to machine settings could further improve the ability of the process to consistently produce parts within the required tolerances.

The capability analysis therefore provided valuable information for guiding future process improvements and machine calibration activities.

4.6 Continuous Improvement Using the PDCA Cycle

The implementation of the production planning system and statistical process monitoring tools was guided by the Plan-Do-Check-Act (PDCA) cycle, which provides a structured framework for continuous improvement. During the planning phase, the production system was analysed using value stream mapping and operational observations to identify inefficiencies. In the implementation phase, the hybrid production planning system and SPC tools were introduced. The checking phase involved evaluating the effectiveness of these changes using control charts and capability analysis. Finally, the action phase focused on implementing corrective measures and refining the production planning system based on the insights obtained from the statistical analysis.

The use of the PDCA cycle ensured that improvements were implemented systematically and that the production system could continue to evolve based on operational feedback and performance data.

4.7 Performance Improvements

The integration of production planning and statistical quality monitoring resulted in measurable improvements in the management of the production process. The structured planning system improved coordination between machining operations and reduced uncertainty in job scheduling. At the same time, the use of statistical monitoring provided objective information about process behaviour and enabled early detection of potential quality problems.

Operational observations indicated improvements in several key performance indicators. Production lead times were reduced due to improved scheduling and reduced waiting times between machining operations. Work-in-progress inventory became easier to monitor, which improved production visibility and reduced delays caused by misplaced or incomplete job information. In addition, the implementation of statistical monitoring allowed the company to detect variations in the machining process more quickly and implement corrective actions before defects occurred.

Overall, the results demonstrate that the integration of structured production planning tools with statistical quality control methods can significantly improve operational performance in small job-shop manufacturing environments. Even relatively simple engineering tools, when applied systematically, can provide substantial improvements in both production efficiency and product quality.

6. Conclusion

This study investigated the development and implementation of an integrated production planning and quality management framework within a job-shop manufacturing environment. The research addressed common operational challenges faced by small manufacturing enterprises, including inefficient production scheduling, limited visibility of work-in-progress, and insufficient monitoring of process variability.

The study demonstrated that the integration of structured production planning tools with statistical quality control techniques can significantly improve manufacturing system performance. The application of value stream mapping enabled the identification of inefficiencies within the production flow, while the Analytic Hierarchy Process provided a systematic method for selecting an appropriate production planning strategy. The implementation of spreadsheet-based planning tools improved production coordination by providing better visibility of job progress and work-in-progress status.

In addition, the introduction of statistical process control techniques allowed the machining process to be monitored using quantitative data. Control chart analysis provided insights into process stability, while process capability analysis evaluated the ability of the manufacturing process to meet required tolerance limits. The use of the PDCA improvement cycle ensured that process improvements were implemented in a structured and iterative manner.

Overall, the results demonstrate that relatively simple industrial engineering tools, when applied systematically, can produce significant improvements in production efficiency and product quality within small manufacturing enterprises.

References

Adamiecki, K., Organisation and Management of Industrial Production, Wydawnictwo Naukowe, Warsaw, Poland, 1913.

Baker, K.R., Introduction to Sequencing and Scheduling, John Wiley & Sons, New York, USA, 1974.

Buzacott, J.A. and Shanthikumar, J.G., Stochastic Models of Manufacturing Systems, Prentice Hall, Englewood Cliffs, NJ, USA, 1993.

Chen, F., Drezner, Z., Ryan, J.K. and Simchi-Levi, D., Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information, *Management Science*, vol. 46, no. 3, pp. 436–443, 2000.

Fanti, M.P., Palumbo, F. and Settineri, L., Job-shop scheduling in Industry 4.0 environments: A literature review, *Computers & Industrial Engineering*, vol. 137, p. 106036, 2019.

Gantt, H.L., Work, Wages, and Profits, Engineering Magazine, New York, USA, 1910. Ishizaka, A. and Labib, A., Review of the main developments in the analytic hierarchy process, *Expert Systems with Applications*, vol. 38, no. 11, pp. 14336–14345, 2011.

Jain, A. and Meeran, S., Deterministic job-shop scheduling: Past, present and future, *European Journal of Operational Research*, vol. 113, no. 2, pp. 390–434, 1999.

Juran, J.M. and Godfrey, A.B., Juran's Quality Handbook, 5th ed., McGraw-Hill, New York, USA, 1999.

Liker, J.K., The Toyota Way: 14 Management Principles from the World's Greatest Manufacturer, McGraw-Hill, New York, USA, 2004.

Montgomery, D.C., Introduction to Statistical Quality Control, 9th ed., John Wiley & Sons, Hoboken, NJ, USA, 2020.

Panneerselvam, R., Production and Operations Management, 2nd ed., Prentice Hall India, New Delhi, India, 2012.

Pinedo, M.L., Scheduling: Theory, Algorithms, and Systems, 5th ed., Springer, New York, USA, 2016.

Rother, M. and Shook, J., Learning to See: Value Stream Mapping to Add Value and Eliminate MUDA, 2nd ed., Lean Enterprise Institute, Brookline, MA, USA, 2003.

Ross, P.J., Taguchi Techniques for Quality Engineering, 2nd ed., McGraw-Hill, New York, USA, 2016.

Saaty, T.L., The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation, McGraw-Hill, New York, USA, 1980.

Slack, N., Chambers, S. and Johnston, R., Operations Management, 10th ed., Pearson, Harlow, UK, 2022.Wheeler, D.J. and Chambers, D.S., Understanding Statistical Process Control, 2nd ed., SPC Press, Knoxville, TN, USA, 2010.

Womack, J.P., Jones, D.T. and Roos, D., The Machine That Changed the World, Free Press, New York, USA, 1990.

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