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MANUFACTURE
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Automated Throughput Optimisation: A Cost Effective I4.0 Solution

Abstract

The escalating consumer demand for cost-effective, high-quality products has compelled manufacturers to enhance efficiency while curbing expenses. The emergence of Industry 4.0 (I4.0) technologies has ushered in an era of closed loop manufacturing, enabled by real-time data processing and feedback. However, the prohibitive costs of I4.0 tools often restrict access for smaller manufacturers and machine shops. Additionally, the shift to I4.0 necessitates a distinct skill set, further disadvantaging smaller players.

This research proposes an innovative approach leveraging existing resources. By introducing a method that integrates a touch trigger probe with aging, albeit, functional CNC machines, establishing a closed loop system. Through intelligent G-code utilisation, this system automates the recording and management of Process Control Indicators (PCIs) while optimising inspection frequencies and throughput. By adopting this method, manufacturers can embrace I4.0 methodologies without the burden of substantial capital expenditure or extensive workforce upskilling. This study not only offers an immediate solution for manufacturers but also serves as a pioneering model for wider I4.0 adoption. By highlighting the potential of repurposing existing machinery, this research highlights a path toward increased efficiency, competitiveness, and accessibility in the manufacturing landscape.

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List of Abbreviations

I4.0 - **Industry 4.0**
Fourth Industrial Revolution focusing on the digitisation of manufacturing

CNC - **Computer Numerical Control**
A method of controlling machine tools & 3D printers allowing automated production

PCI - **Process Capability Indexes**
A measure of a processes ability to manufacture goods within a set specification

C_p- **Process Capability**
A statistical measure of a process's ability to produce output within specification limits.

Cp_K- **Process Capability Index**
A focused look at process capability with an emphasis on centring

P_p- **Process Performance**
A statistical measure that evaluates a processes ability to produce output within specified limits focusing solely on the process’s inherent variability

Pp_K- **Process Performance Index**
A statistical measure that evaluates a process's ability to produce output within specified limits. It focuses solely on the process's inherent variability

NCU- **Numerical Control Unit**
The control unit of a CNC machine responsible for interpreting G-code and control the machines kinematics

SPC- **Statistical Process Control**
A data-driven methodology for monitoring, analysing, and controlling manufacturing processes to ensure consistent product quality

EPC- **Engineering Process Control**
A method of monitoring and adjusting process variables to maintain a desired output

CMM- **Coordinate Measing Machine**
A device that measures the geometry of physical objects by sensing discrete points on the surface of the object with a probe

SME- **Small and Medium-sized Enterprises**
Companies that employ fewer than 250 people and have a turnover of less than €50 million or an annual balance sheet total of less than €43 million

ECTIB- **Engineering Construction Industry Training Board**
UK-based organisation that focuses on providing skills, standards, and qualifications for the engineering construction industry

CAPP- **Computer Aided Production Planning**
The use of computer technology to aid in the process planning of a part or product in manufacturing

DT- **Digital Twin**
A digital twin is a virtual representation of a physical object or process, contextualised in a digital version of its environment

CPS- **Cyber Physical Systems**
The integration of computation, communication, and control to achieve the desired performance of physical processes

STEP-NC **Standard for the Exchange of Product model data**
A standard for CNC machines making use of bi-directional data transfer for productivity improvements

1. Introduction

In the pursuit of cost-effective, high-quality manufacturing, the contemporary industrial landscape is witnessing a transformative shift in both production processes and inspection methodologies (Blecha, et al., 2022). The increasing demand for such products is compelling manufacturing enterprises to drive down costs and enhance operational efficiencies. This demand, coupled with the integration of Industry 4.0 (I4.0) technologies, offers a myriad of possibilities for achieving heightened efficiencies and reduced costs.

However, the adoption of these advancements is not without challenges. The incorporation often necessitates significant investments in new, technologically advanced equipment (Amaral, et al., 2019). This predicament places small manufacturing entities, particularly those with narrow profit margins, at a distinct disadvantage, hindering their ability to keep pace with technological advancements and maintain competitiveness. Consequently, operational constraints are imposed on older but still functional CNC machining centres.

For smaller enterprises to sustain competitiveness, the consideration of equipment upgrades becomes imperative, leveraging the potential offered by advancements in manufacturing processes (Pollak, et al., 2020). However, this necessitates navigating the skills gap, wherein traditional manufacturing expertise may not align with the demands of I4.0 technologies (Hall, et al., 2023). Consequently, small companies may face the dilemma of either reskilling their existing workforce or augmenting their teams with individuals whose roles might not directly impact day-to-day manufacturing operations. Both alternatives present financial challenges that could further diminish already modest profit margins (Abdelmajied, 2022). Alternatively, companies may choose to forgo these investments, potentially jeopardising long-term competitiveness, and future viability by resisting the adoption of contemporary practices and technologies (Dassisti, et al., 2019).

In the context of CNC-related manufacturing processes, measuring process capability indexes (PCI) is not novel. Renishaw's commercially available software utilises touch probes to furnish dimensional and PCI information (Renishaw plc., 2016). However, a notable limitation is that this software exclusively functions with newer CNCs operating on Windows-based controllers, necessitating an investment in new machinery to exploit its features.

A forward-looking approach involves the configuration of stored variables within a CNC controller, the execution of predetermined calculations, and the precise formatting and placement of variables within G-code and Macro B programs (Djassemi, 1998). This strategic implementation facilitates the establishment of a closed-loop system, empowering a CNC to autonomously optimise inspection frequency and throughput based on PCI values calculated and collected by the CNC itself (Tseng, et al., 2005). This innovative system minimises the need for human intervention or distinct data collection processes, thereby streamlining operational efficiency in CNC-related manufacturing and allowing the adoption of I4.0 methodologies while utilising existing machinery and current skillsets.

1.1. Aims

The aim of the research is to enhance the functionality and efficiency of existing CNC machine tools for small manufacturing companies or SMEs by implementing a closed-loop system using touch trigger probes. This methodology involves developing steps to apply the logic required to utilise a touch trigger probe in existing G-code programs, thereby aiding in throughput optimisation. The research also includes the selection of different PCIs to best suit a given manufacturing process and a test to ensure the suitability of a CNC machining centre for a dependable closed-loop system.

The use of touch trigger probes in closed-loop systems for CNC machines has been the subject of several academic studies, demonstrating their potential benefits and applications. Here are further details from the provided academic references:

- Modelling and Analysis between In-Process CNC Touch Probe Gauging and Post-Process CMM Inspection (Tseng, et al., 2005).
  The paper investigates the closed-loop measurement error in CNC milling in relation to in-process gauging using a touch probe and post-process inspection using a coordinate measuring machine (CMM). The study aims to understand the factors affecting the measurement errors and the potential for improving production efficiency and part quality. The research is significant as it addresses the shift towards 100%-part inspection for zero defects in the discrete part manufacturing industry. The use of a machine-mounted touch probe is explored as a means to enable real-time automatic tool offset correction and improve process control. The analysis results demonstrate the potential for enhancing production efficiency and part quality. The paper provides valuable insights into the integration of in-process gauging and post-process inspection in CNC milling, with implications for manufacturing quality and efficiency.

- On-Machine Measurement System Implemented Based on Fanuc CNC System Using a Touch Trigger Probe (Zhang & Wang, 2014)
  The paper aims to implement an on-machine measurement (OMM) system using a touch trigger probe installed on the spindle of a milling machine with a Fanuc 0i-mc CNC system. It presents the hardware system configuration for OMM and its software, including the generation of measurement programs based on CAD models of workpieces.

- Machining Error Compensation of Single Shaft Part Based on Touch Trigger Probe (Li, et al., 2017)
  This study addresses the error compensation problem of single shaft part machining by proposing a method that involves testing the dimensional accuracy of the workpiece using a touch trigger probe. Based on the measurement results, a least squares mathematical model of machining error is established, and error compensation is performed in the finishing stage using CNC macro programs. The method aims to integrate online detection, error compensation, and precision evaluation to improve processing efficiency and quality.

- Comparative Performance Evaluation of Multiconfiguration Touch-Trigger Probes for Closed-Loop Machining of Large Jet Engine Cases #4
  The article presents advances in the methodology of rapidly comparing various probe configurations for closed-loop machining of large jet engine cases. The study investigates the measurement capability of different probe configurations for use in manufacturing environment conditions, providing insights into the repeatability, reproducibility, and error of various probe configurations.

- Gear Coordinate Measurement Onboard CNC Machine With Touch-Trigger Probe (Tan, 2005)
  This study discusses the feasibility and benefits of performing gear coordinate measurement onboard multi-axis CNC machines using touch-trigger probes. It addresses issues related to converting machine coordinates to gear tooth deviations and minimising the impact of system errors on measurement accuracy.

- Capability assessment of CNC machining centres as measuring devices (Holub, et al., 2018)
  The paper focuses on the use of CNC machining centres as measuring devices for assessing length dimensions using workpiece touch probes. The study evaluates the capability of CNC machining centres to perform measurements, particularly in the context of length dimension assessment. The research is significant as it addresses the potential dual role of CNC machining centres in both manufacturing and metrology, offering insights into

their use as measuring devices. The paper contributes to the understanding of the capabilities of CNC machining centres in performing accurate measurements, which is essential for ensuring quality and efficiency in manufacturing processes.

These references offer valuable insights into the implementation and benefits of touch trigger probes in closed-loop systems for CNC machines, covering various aspects such as dimensional metrology, on-machine measurement, error compensation, and comparative performance evaluation of different probe configurations.

1.2. Objectives

The aims of this research will be achieved through experimentation and testing of existing CNC equipment and already commercially available probing cycles.

- Developing an Innovative Integration Method:
  Investigate and develop a method to integrate a touch trigger probe with functional yet aging CNC machines to establish a closed-loop system for real-time data processing and feedback.

- Automating Process Control Indicators (PCIs) Management:
  Implement intelligent G-code utilisation to automate the recording and management of Process Control Indicators (PCIs) within the manufacturing process. Focus on optimising inspection frequencies and throughput.
- Enhancing Accessibility and Affordability:
  Enable smaller manufacturers to adopt I4.0 methodologies without substantial capital expenditure or extensive workforce upskilling. Provide an accessible and cost-effective solution by repurposing existing machinery.
- Demonstrating Feasibility and Immediate Benefits:
  Demonstrate the feasibility and immediate benefits of the proposed method in terms of increased efficiency, reduced expenses, and enhanced competitiveness for manufacturers.
- Pioneering a Model for Wider Adoption:
  Establish a pioneering model for wider adoption within the manufacturing landscape. Highlight the potential of repurposing existing resources as a path toward increased efficiency, competitiveness, and accessibility for both small and large-scale manufacturers.

By achieving these objectives, this research endeavours to contribute valuable insights and practical solutions to the manufacturing industry, fostering a change in basic assumptions towards more inclusive and sustainable Industry 4.0 adoption.

1.3. Justification

I4.0 has ushered in new technologies and tools that can help manufacturing companies improve their performance and gain tighter control over their processes by automating process improvements and optimisation through data gathering and processing (Pollak, et al., 2020). The adoption of I4.0 can be very advantageous if a company is able to accommodate the high costs of integrating the often-expensive equipment that is required and have the necessary skills available already employed (Lu, et al., 2020). This leaves an ever-growing gulf between those who can afford I4.0 adoption, and those who can't. This can leave many smaller players in the manufacturing industry falling behind to a point where they cannot catch up (Glass, et al., 2018).

What these smaller players often overlook is that the equipment and skills necessary to adopt I4.0 methodologies are already in place to start making efficiency gains and become more competitive (Dassisti, et al., 2019). There have been many academic roadmaps written regarding the implementation and barriers of I4.0 (Chauhan, et al., 2021), there have been few that deal with solely with SMEs (Masood & Sonntag, 2020). Strategic models have been developed with methodologies that have yielded successful results (Pinto, et al., 2019). However, larger companies seem better placed to adapt to the challenges of adopting I4.0 (Stentoft, et al., 2019).

This research intends to set out how existing CNC machining centres can be used to gain extra functionality without the need for extra equipment, training, or services from outside vendors while opening the door to further I4.0 adoption.

1.4. Limitations

This research will not focus on improving the probing and inspection accuracy of CNC machine tools, nor will it be used as a justification for the removal of pre-existing inspection methodologies and practices. Additionally, no new inspection probing cycles will be derived from the research. These limitations are important to consider when evaluating the scope and potential impact of the research.

Expanding on these limitations, it's crucial to acknowledge that the research will rely on existing equipment and probing cycles, which may limit the extent to which the CNC machine tool can automatically react to changes in the PCI data. Furthermore, the exclusion of new inspection probing cycles from the research may restrict the development of novel methods for enhancing the machine's inspection accuracy. It's important to recognise that these limitations may affect the practical applicability of the proposed method. While the focus on leveraging existing resources is a pragmatic approach, it's essential to consider the potential trade-offs in terms of the method's adaptability to diverse CNC machine tools and its ability to address future advancements in probing and inspection technologies.

The limitations mentioned are essential for understanding the scope and potential impact of the research. They underscore the need for future studies to address the excluded aspects and broaden the scope of the proposed method.

1.5. Methodology

This research is designed to provide a comprehensive strategy for small manufacturing companies to improve the functionality and efficiency of their existing CNC equipment, while also paving the way for broader Industry 4.0 adoption. The research will primarily adopt a quantitative approach, involving comparisons between figures calculated via spreadsheet or MiniTab and those computed on aging CNC machines to assess their suitability for use. The CNC to be used in this research is a Mori-Seiki NV5000 α 1A/40 that has been used in the manufacture of heat resistant superalloys since its commissioning in June 2004.

Furthermore, the methodology will involve conducting dimension verification on pre-manufactured test pieces using a calibrated coordinate measuring machine (CMM) to establish a baseline for comparison against the CNC. This step will provide valuable insights into the accuracy and precision of the CNC equipment, enabling a thorough assessment of its performance.

The data collected from the CNC machine will be subjected to rigorous analysis using various statistical methods to derive insights and optimise production processes and determine suitability. Statistical analysis will be conducted on the gathered data, and the results will be presented through graphs or visual aids, where applicable. This approach will facilitate a deeper understanding of the performance of the CNC equipment and provide actionable insights for process optimisation.

It's important to note that the sample size for all tests carried out in this research will be a minimum of 30, ensuring statistical robustness and reliability of the findings.

2. Industry 4.0 and Manufacturing

2.1. What is Industry 4.0

Industry 4.0, also known as the Fourth Industrial Revolution or I4.0, represents the next phase in the digitisation of the manufacturing sector (Pollak, et al., 2020). It is characterised by the integration of digital-based technologies in the production process to increase enterprise efficiency. The concept of Industry 4.0 was practically non-existent before 2014, but by 2019, 68 percent of respondents to a McKinsey global survey regarded it as a top strategic priority (McKinsey & Company, 2023). This revolution is driven by disruptive technologies such as the Internet of Things (IoT), cloud computing, analytics, artificial intelligence (AI), and machine learning. These technologies enable the development of smart factories equipped with advanced sensors, embedded software, and robotics that collect and analyse data, leading to increased automation, predictive maintenance, and process optimisation. Industry 4.0 aims to achieve mass customisation and efficiency across the value chain, ultimately transforming every industry to a greater or lesser degree.

The phrase "Industry 4.0" was first introduced in 2012 in Germany as part of the country's High-Tech Strategy 2020, with the goal of evaluating scientific alterations in manufacturing and maintaining global competitiveness (Pollak, et al., 2020). The term "4.0" signifies the fourth industrial revolution, which involves an integrated approach to connectivity, data usage, and significant insights across various business operations, including the value chain (Singh, 2021). The implementation of artificial intelligence and decision-making aids companies in optimising the automation and production process.

The economic and social impacts of Industry 4.0 have been the subject of extensive research. Various studies have explored the implications of Industry 4.0 on sustainable development, circular economy, global value chains, and capability development in manufacturing subsidiaries (Abdelmajied, 2022). Additionally, research has focused on the technological elements of artificial intelligence, the meaning of I4.0 to supply chains, and the intersection of circular economy and I4.0.

Industry 4.0 is built on several key technological advancements that enable the transformation of traditional manufacturing processes. These concepts include:

- Internet of Things (IoT): The integration of physical devices, sensors, and software systems through the internet enables real-time data collection and analysis. This interconnectedness allows for seamless communication and collaboration between machines, products, and humans (Younan, et al., 2020).
- Big Data and Analytics: The ability to capture and analyse large volumes of data allows manufacturers to make informed decisions, optimise production processes, and improve quality control. By harnessing the power of data, companies can gain valuable insights into their operations, enabling them to identify areas for improvement and drive innovation (Singh, 2021).
- Artificial Intelligence (AI) and Machine Learning: AI algorithms and machine learning models enable autonomous decision-making, predictive maintenance, and robotic automation. These technologies empower machines to learn from data, adapt to changing circumstances, and perform tasks with minimal human intervention (Rai, et al., 2021).
- Cyber-Physical Systems (CPS): The integration of physical and digital systems creates a seamless connection between machines, products, and humans, enabling real-time monitoring and control. This integration allows for the optimisation of production processes, improved safety measures, and increased efficiency (Tao, et al., 2019). These technologies are revolutionising the manufacturing sector by enabling real-time data analysis, increased automation, predictive maintenance, and improved decision-making, ultimately leading to greater efficiency and productivity across the value chain.

The future of manufacturing is being transformed by several significant developments. Smart factories, a product of Industry 4.0, are creating interconnected environments where machines, products, and humans are linked, enabling real-time monitoring, predictive maintenance, and self-optimising production processes (Hermann, et al., 2015). These factories leverage advanced technologies such as IoT, AI, and CPS to create highly efficient and adaptive manufacturing environments. Collaborative robotics, also known as cobots, are integrating robots and humans in the manufacturing process, leading to collaborative and flexible production systems. This integration allows robots to assist human workers rather than replacing them, enabling human workers to focus on tasks that require creativity, problem-solving, and decision-making (Javaid, et al., 2022). Digital supply chains, facilitated by Industry 4.0, are enhancing transparency, traceability, and agility in manufacturing. They enable real-time inventory management, demand forecasting, and supplier integration, allowing companies to respond quickly to market changes, optimise inventory levels, and enhance customer satisfaction (Rafael, et al., 2020). Furthermore, decentralised manufacturing, made possible by 3D printing and additive manufacturing technologies, is reducing transportation costs, and enabling local production. This approach allows for on-demand production, customisation, and reduced lead times, empowering companies to respond swiftly to customer demands and market trends (Lu, et al., 2020). I4.0 technologies have a significant impact on various aspects of manufacturing, including productivity, quality control, customisation, and sustainability. These technologies streamline production processes, reduce downtime, and minimise errors, leading to improved operational efficiency and cost savings (Holub, et al., 2018). By automating repetitive tasks and optimising workflows, companies can achieve higher levels of productivity and resource utilisation. Automation and robotics eliminate repetitive tasks, allowing workers to focus on more complex and creative tasks, leading to higher productivity levels and increased innovation. Real-time data collection and analysis enable manufacturers to detect and address quality issues at an early stage, ensuring higher product quality and customer satisfaction (Oborski, 2014). I4.0 also enables mass customisation by leveraging digital technologies to tailor products to individual customer needs and preferences, enhancing customer satisfaction and loyalty. Moreover, it promotes resource efficiency, waste reduction, and energy optimisation, leading to more sustainable manufacturing practices (Zhou & Smulders, 2021).

The use of Industry 4.0 technologies, such as augmented reality, smart devices, and embedded intelligence, has been shown to improve machine efficiency, reduce the risk of poor inventory management, and predict the skills needed by operators on site. This results in more flexible, agile, and responsive intelligent factories. Leading manufacturers are realising significant value from data and analytics, AI, and machine learning, which has led to increased production capacity, reduced material losses, improved customer service, and higher employee satisfaction (Dogan & Birant, 2021). However, many companies are still struggling to capture the full potential of their transformation efforts or deliver a satisfactory return on investment. Nevertheless, Industry 4.0 is expected to make production systems faster and more efficient, elevate mass customisation to new levels, and fundamentally transform a company's competitive position by improving flexibility, speed, productivity, and quality of the production process (Pollak, et al., 2020).

In conclusion, Industry 4.0 represents a significant shift in the manufacturing sector, driven by the integration of digital technologies to enhance efficiency, automation, and customisation across the value chain. The concept has gained widespread attention and is considered a top strategic priority for many companies. Academic research has delved into the economic, social, and technological implications of Industry 4.0, highlighting its potential to transform various industries and drive sustainable development.

2.2. Growth and Adoption of Industry 4.0

The adoption of Industry 4.0 technologies and tools has been a significant focus for organisations across various industries. Industry 4.0, also known as the fourth industrial revolution, is characterised by the integration of digital technologies, data analytics, and automation in manufacturing and other industrial sectors (Rafael, et al., 2020). This transformative wave has led to the emergence of smart factories, where cyber-physical systems, the Internet of Things (IoT), and cloud computing are seamlessly integrated to create more efficient and flexible production processes (Singh, 2021).

2.2.1. Growth and Adoption

The "Adoption of Industry 4.0 Technologies Through Continuous Improvement" chapter (Sessa, et al., 2022), provides valuable insights into the current state of adoption of smart factory technologies. The chapter identifies different tools to support continuous improvement of performance in order to adopt the Industry 4.0 model, highlighting the strategies, key performance indicators (KPIs), decision-making frameworks, use case adoption, deployment, vendors, and challenges associated with Industry 4.0 adoption.

A study published in the Annals of Operations Research (Research and Markets, 2023), categorises the main Industry 4.0 technologies based on their adoption stages, providing insights into the maturity levels of adoption. The study employs a structured literature analysis considering Industry 4.0 technologies and their adoption stages to identify the technology adoption stage for each technology type, which in turn supports a maturity level categorisation.

2.2.2. Market Dynamics and Sales Data

The "Global Industry 4.0 Market Report 2023" highlights the rise in the adoption of industrial robots as a key driver of growth in the Industry 4.0 market. Industrial robots play a crucial role in automating manufacturing processes, enhancing productivity, and enabling the seamless integration of different components within smart factory environments. The report also emphasises the transformative impacts of Industry 4.0 technologies on various sectors such as manufacturing, automotive, oil and gas, and energy (Paraskevopoulos & Wegner, 2022).

In terms of sales data, the global market for Industry 4.0 technologies is experiencing robust growth. The increasing demand for advanced manufacturing solutions, predictive maintenance, and real-time data analytics is driving the adoption of Industry 4.0 technologies across different industrial verticals. According to a market research firm, the global Industry 4.0 market is projected to reach a value of USD 156.6 billion by 2024, with a compound annual growth rate (CAGR) of 15.7% during the forecast period (Paraskevopoulos & Wegner, 2022).

2.2.3. Academic Perspectives and Research Contributions

Academic research plays a crucial role in understanding the adoption and implications of Industry 4.0 technologies. The study published in the Annals of Operations Research (Research and Markets, 2023), provides essential contributions to scholars and practitioners by categorising the main Industry 4.0 technologies in terms of their adoption stage and identifying critical hot topics, proposing a well-articulated research agenda.

Another area of academic research focuses on the potential implications of Industry 4.0 technologies for environmental sustainability (Javaid, et al., 2022). A literature review-based research aims to identify how Industry 4.0 technologies can improve environmental sustainability by reducing energy consumption, minimising waste, and optimising resource utilisation. The study highlights the broader implications of technology adoption beyond operational benefits, emphasising the importance of considering environmental factors in the deployment of Industry 4.0 solutions.

2.2.4. Conclusion

In conclusion, the adoption of Industry 4.0 technologies and tools is a rapidly evolving landscape, with reports and academic research providing valuable insights into the current state of adoption, key drivers of growth, technology categorisation, and potential implications for sustainability. The available resources offer a comprehensive understanding of the adoption growth of Industry 4.0 technologies, encompassing both industry-specific data and academic perspectives. As organisations continue to embrace digital transformation and smart manufacturing practices, the adoption of Industry 4.0 technologies is expected to further accelerate, reshaping the future of industrial production, and creating new opportunities for innovation and growth (Stentoft, et al., 2019).

The growth and adoption of Industry 4.0 have been significant, with the market size and adoption rates reflecting the increasing integration of digital technologies in the manufacturing sector. According to a report by Fortune Business Insights, the global industry 4.0 market size was valued at $114.55bn in 2021 and is projected to grow from $130.90bn in 2022 to $377.30 bn by 2029 (Fortune Business Insights, 2022). This substantial growth underscores the transformative impact of Industry 4.0 technologies on the manufacturing industry, driving efficiency, automation, and customisation across the value chain.

In the UK, the adoption of I4.0 technologies has been a topic of interest, with UK manufacturers seeing Industry 4.0 as an opportunity to revolutionise the manufacturing sector (KPMG, 2017). However, there is a noted concern about whether UK manufacturers have a coherent strategy and the right talent and skills to capitalise on this opportunity. This highlights the importance of addressing the skills gap and preparing the workforce for the adoption of Industry 4.0 technologies in the UK (Hall, et al., 2023).

2.3. Closed Loop manufacturing and its Advantages

The concept of closed loop feedback in manufacturing processes is closely intertwined with the principles of the circular economy, which seeks to minimise waste and optimise resource utilisation. The circular economy is a sustainable paradigm that aims to achieve this by "slowing, closing, and narrowing material and energy loops," involving practices such as long-lasting design, maintenance, repair, reuse, and remanufacturing (Zhou & Smulders, 2021).

In the context of manufacturing, closed loop feedback involves the systematic collection and utilisation of data from various stages of production to improve efficiency, quality, and sustainability (Oborski, 2014). Unlike traditional linear manufacturing systems, closed loop feedback integrates real-time information and analysis into the production cycle, creating a continuous loop of improvement. This concept is closely aligned with the principles of the circular economy, as it enables manufacturers to identify inefficiencies, minimise waste, and make data-driven choices to enhance overall efficiency and sustainability (Wrinkler, 2011).

The integration of closed loop feedback with Industry 4.0 technologies, such as big data, cyber-physical systems, and the Internet of Things (IoT), plays a crucial role in enabling manufacturers to create a seamless and interconnected manufacturing process. This integration allows for real-time monitoring, data-driven decision-making, and continuous refinement of products and processes, ultimately leading to improved efficiency and reduced waste (Bousdekis, et al., 2020).

The integration of Industry 4.0 technologies with closed loop feedback in manufacturing offers several benefits, including:

- Improved Operational Efficiency: The combination of closed loop feedback and Industry 4.0 technologies, such as machine learning, enables faster decision-making, better response times, and higher efficiency. Machine learning algorithms can predict equipment failure with high accuracy, leading to improved asset reliability and better product quality (Terziyan, et al., 2018).

- Autonomous Operation and Reduced Latency: Closed loop systems offer autonomous operation, which eliminates labour costs for manual intervention, and reduced latency for faster reaction times. This results in improved operational efficiency and greater productivity.
- Enhanced Sustainability: The integration of closed loop feedback with Industry 4.0 technologies can contribute to sustainability by enabling manufacturers to continuously monitor and analyse production data, identify inefficiencies, and optimise resource utilisation. This can lead to reduced energy consumption, lower emissions, and minimised material wastage, ultimately creating a greener and more sustainable manufacturing environment (Kumar, et al., 2020).
- Seamless Record-Keeping and Traceability: Industry 4.0 enables seamless record-keeping and traceability, which can speed up traceability, limit liabilities, warranty costs, and recalls. The automated closed-feedback loop inherent in Industry 4.0 contributes to this seamless record-keeping, ultimately improving operational efficiency (Danjou, et al., 2017).

Closed loop feedback in manufacturing processes represents a fundamental shift towards sustainable and efficient production, aligning with the principles of the circular economy. By harnessing real-time data and feedback, manufacturers can optimise their operations, reduce environmental footprint, and meet customer demands effectively (Zhou & Smulders, 2021). As industries continue to evolve, integrating closed loop feedback mechanisms will be essential in creating a circular, sustainable, and customer-focused manufacturing ecosystem.

3. Challenges Facing Manufacturers in Adopting Industry 4.0

3.1. The Cost of Adopting Industry 4.0

The advent of Industry 4.0 and the integration of digital technologies and advanced automation into manufacturing processes has promised improvements in productivity, efficiency, and competitiveness for industries worldwide (Castelo-Branco, et al., 2019). However, the transition towards Industry 4.0 is not without its challenges, with one of the most prominent being the high cost associated with implementing new machinery and technologies (Abdelmajied, 2022).

As with most investments in manufacturing, the upfront costs of new equipment are one of the biggest costs associated with adopting I4.0 technologies. The initial capital required for acquiring Industry 4.0 machinery can be substantial. Depending on the size of a company and the industry in which it operates, the upfront costs of I4.0 technologies can range from £10,000 to £1 million (Paraskevopoulos & Wegner, 2022). Many SMEs choose to work with consultants to help develop plans and strategies in adopting I4.0 technologies (Issa, et al., 2018). These costs are often incurred prior to purchasing any new equipment but if done correctly it can limit the impact of integration and compatibility issues later in a project (Dassisti, et al., 2019). Ensuring the seamless integration and compatibility of new machinery with existing systems is a complex and costly endeavour. Incompatibility issues may necessitate customisations, retrofits, or even a complete overhaul of existing equipment and systems (Dassisti, et al., 2019). These integration challenges contribute significantly to the overall implementation costs. Many businesses will have systems in place that will need to be integrated with I4.0 technologies. This can be a complex and expensive process, especially for businesses with older systems. The cost of integration can vary depending on the complexity of the systems and the amount of customisation required.

The ongoing maintenance and management of Industry 4.0 machinery and systems are critical to their long-term success. I4.0 technologies would require regular repairs and replacements. Though, this is still the case with existing technologies already in place within a company. I4.0 may also require software updates, due to the nature of I4.0 technology being mainly data generative, and data driven. This can increase a company's maintenance budget (Dassisti, et al., 2019). But another issue facing a company would be the rate of technological advancement. As more advanced technologies emerge, companies may have to upgrade their existing machinery or invest in entirely new systems to remain competitive or even operational (Castelo-Branco, et al., 2019). Technological obsolescence requires continuous investment and can be a costly process, especially for SMEs. The rapid pace of technological advancements is a key driver behind the high cost of implementing Industry 4.0 machinery. There are a number of factors that contribute to technological obsolescence. One factor is the rapid pace of technological innovation. New technologies are being developed all the time, and these new technologies often offer significant advantages, often at the cost of said older technologies falling out of production (Abdelmajied, 2022).

These costs can increase further should there be a need to retrain employees on any new equipment or technology. With the nature of I4.0 being more related to data generation and processing, these training costs may require employees to undertake higher education courses (Rüßmann, et al., 2023). This not only increases the costs further than more traditional technologies but can also impact the time taken for an SME to fully utilise the technology and begin reaping any benefits.

3.2. Skill Levels

Manufacturing is a vital part of the UK economy. Employing over 2.5 million people, manufacturing makes up for over 10% of the UK GDP. However, a recent report by MakeUK has found that 36% of vacancies in manufacturing are unfilled due to applicants lacking the necessary skills, appropriate qualifications, or relevant experience (MakeUK, 2022). The manufacturing sector is not alone in this, as other industries face the same challenges. It should be noted that the average across all other industries is currently lower at 24%. This skills gap is more prominent at the technician and skilled operator level.

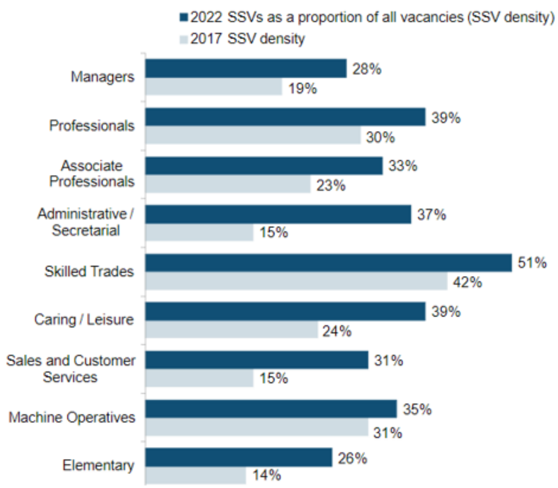

Figure 1 - Open Vacancies per Industry (OSR, 2023)

Around 44% of employers have reported gaps in required skills and knowledge in these job types. This seemingly coincides with the declining rates of manufacturing apprenticeships. Apprenticeship rates have dropped from 14 per 1,000 employees in the year 2018/2019, to 12 per 1,000 employees in 2020/2021 (GOV.UK, 2023). The UK has seen a decrease in manufacturing employment besides apprenticeships. Since 2013, employment within the UK manufacturing sector has decreased to 2.54 million from 2.67 million in 2013. This represents a decline of 4.9% over the same period (OSR, 2023).

Year	Employment Level (Million)	Change (%)
2013	2.76	-
2014	2.65	-0.8%
2015	2.63	-0.7%
2016	2.59	-1.5%
2017	2.56	-1.1%
2018	2.54	-0.8%
2019	2.53	-0.4%
2020	2.49	-1.6%
2021	2.52	+1.2%
2022	2.53	+0.4%
2023	2.54	+0.4%

Figure 2 - Employment Level in Manufacturing (OSR, 2023)

The COVID-19 pandemic can be attributed to the largest decline in manufacturing employment. However, the 1.6% drop is more than made up for in the years 2021 to 2023, with numbers slightly above pre-pandemic levels (GOV.UK, 2023). The table below shows that almost every other industry or sector has grown in the last ten years whereas manufacturing has contracted significantly.

Sector	Employment level (millions) in 2013	Employment level (millions) in 2023	Change from 2013 (%)
Manufacturing	2.67	2.54	-4.90%
Construction	2.23	2.31	+3.6%
Wholesale and retail trade	3.5	3.6	+2.9%
Accommodation and food service activities	1.83	1.9	+3.8%
Transportation and storage	1.19	1.24	+4.2%
Information and communication	1.07	1.09	+1.9%
Financial and insurance activities	1.03	1.04	+1.0%
Professional, scientific, and technical activities	2.06	2.2	+6.8%
Administrative and support service activities	1.62	1.7	+4.9%
Public administration and defence; compulsory social security	2.48	2.56	+3.2%
Education	2.04	2.12	+3.9%
Human health and social work activities	1.79	1.91	+6.7%
Arts, entertainment and recreation	1.39	1.48	+6.5%
Other service activities	0.76	0.82	+7.9%

Figure 3 - Change in Employment by Industry (OSR, 2023)

A reason for this contraction can be the increase in automation in the UK. Figures from the ONS have shown that the stock of industrial robotics in the UK has increased by 5.6% CAGR and sat at roughly 18,300 in 2022. This growth is expected to continue. A report by MakeUK predicts that the levels of industrial robotics and automation in the UK will double by 2030 (MakeUK, 2023). This growth is impacting the manufacturing sector in perhaps a counter-intuitive way. The increase in automation is leading to increased productivity and efficiency but at the cost of human employment. This reduced employment requirement can go on to deter young people from perusing a career in manufacturing due to the job availability, security and pay conditions (Hall, et al., 2023).

3.3. Overcoming the Challenges

The UK government has launched a series of initiatives to tackle the skills gap in the manufacturing sector, recognising the critical importance of a skilled workforce in driving industry growth and innovation. These initiatives encompass various strategies aimed at addressing the challenges posed by the skills shortage and preparing the workforce for the demands of Industry 4.0.

3.3.1. Addressing the Skill Gap

The UK government has proactively introduced a range of initiatives to tackle the skills gap in the manufacturing sector, acknowledging the pivotal role of a proficient workforce in shaping the industry's future. One such initiative is the Manufacturing Skills Plan, a government-led program aimed at bolstering the training and development of individuals pursuing careers in manufacturing. This strategic plan is designed to address the skills shortage in the sector by focusing on providing the necessary skills and knowledge to equip individuals with the competencies required to thrive in the evolving manufacturing landscape.

A key component of the Manufacturing Skills Plan is the emphasis on investing in education and employing the latest technologies to bridge the skills gap and attract the next generation of workers (Rhodes, 2020). This forward-looking approach underscores the government's commitment to modernising the manufacturing workforce and ensuring that it remains competitive and at the forefront of technological advancement. The plan's focus on leveraging innovative technologies and fostering a culture of innovation is instrumental in preparing the workforce to embrace the opportunities presented by Industry 4.0 and other transformative manufacturing trends (Hall, et al., 2023).

To further fortify the industry's talent pool, the UK government, in collaboration with higher learning institutions and industry representatives from across manufacturing, including employer bodies and trade unions, has embarked on a unified effort to address the skills shortage (Glass, et al., 2018). This collaborative approach involves working jointly to deliver targeted action and recover from the effects of Brexit and the Covid-19 pandemic, both of which have had a significant impact on the manufacturing sector. By uniting to assert their commitment to working collaboratively, these stakeholders are striving to address the skills gap and ensure the industry's sustained growth and resilience in the face of ongoing challenges.

The importance of this collaborative approach is underscored by a survey of manufacturing companies, which found that only 34% agreed that colleges and learning providers are meeting their business requirements. This highlights the need for closer collaboration between industry and educational institutions to ensure that the skills and knowledge imparted to students are directly relevant to the evolving needs of the manufacturing sector. Research has shown that STEM graduates lack experience and soft skills (ECITB, 2018). By addressing this mismatch, the industry can enhance the employability of graduates and bridge the skills gap, as reported by the Engineering Construction Industry Training Board (ECITB) in their 2018 report, "The Supply & Demand for Engineers in the UK" (ECITB, 2018).

In conclusion, the UK government's multifaceted initiatives, such as the Manufacturing Skills Plan and collaborative efforts with industry stakeholders, higher learning institutions, and trade unions, reflect a concerted commitment to addressing the skills gap in the manufacturing sector. By investing in education, training, and the latest technologies, and by fostering closer collaboration between industry and educational institutions, the government is working to ensure that the manufacturing workforce is equipped with the necessary skills to drive the industry's continued growth and competitiveness.

3.3.2. Attract and Retain

In the modern era, the manufacturing industry is undergoing a significant transformation, with advancements in technology and changing workforce dynamics presenting a critical challenge for manufacturers: attracting and retaining skilled workers. To address this, several strategies have been identified as essential for UK manufacturers to enhance their ability to attract and retain skilled workers, ultimately strengthening their workforce and positioning themselves for success in an increasingly competitive global market.

One of the most effective ways to attract and retain talent in the manufacturing industry is by offering competitive compensation and benefits packages. This includes providing competitive wages, healthcare benefits, retirement plans, and other benefits that can make the company an appealing employer. The average gross annual earnings of engineering professionals are over £40,000 with engineering apprentices earning over £28,000 in their first year after studying (ECITB, 2018). Skilled workers are more likely to be attracted to companies that offer attractive compensation and benefits, and this can significantly contribute to their retention within the organisation.

Manufacturers can also attract and retain skilled workers by investing in training and development programs. By offering opportunities for upskilling and career advancement, companies can demonstrate a commitment to the professional growth and long-term success of their employees (Abdelmajied, 2022). This investment in the continuous development of the workforce not only addresses the skills gap but also fosters a culture of innovation, efficiency, and adaptability, ultimately ensuring that the UK engineering industry remains robust, competitive, and at the forefront of technological advancement in the years to come (Hennik Research, 2023).

Creating a positive and supportive work environment is crucial for employee retention. This can involve promoting work-life balance, recognising, and rewarding employee contributions, and fostering a culture of collaboration and innovation. A positive workplace culture is a key factor in retaining skilled workers, as it contributes to their overall job satisfaction and engagement within the organisation. 50% of manufacturers stated that flexible working is being offered as a way to recruit and retain staff (MakeUK, 2022). This becomes more attainable as digitisation and the adoption of automation becomes more widespread.

Embracing advanced technologies and automation can also appeal to skilled workers. By demonstrating a commitment to innovation, companies can attract workers who are eager to work with innovative tools and processes. This can contribute to the retention of skilled workers who are motivated by the opportunity to work with the latest technologies and contribute to the advancement of the industry. Furthermore, tailored recruitment campaigns and collaboration with education institutions are essential for attracting and retaining skilled workers. Employers can work closely with educational institutions to tailor recruitment campaigns and offer attractive starting packages to new graduates. This collaboration can help ensure that educational programs are directly relevant to industry needs, enhancing the employability of graduates and addressing the skills shortage.

By implementing these strategies, UK manufacturers can enhance their ability to attract and retain skilled workers, ultimately strengthening their workforce and positioning themselves for success in an increasingly competitive global market.

4. Manufacturing PCIs

4.1. Review of Manufacturing PCI’s

Process capability indexes are essential tools in manufacturing for assessing the ability of a process to produce parts within specified limits (Munro, et al., 2015). They provide valuable insights into the consistency and reliability of manufacturing processes, helping to identify areas for improvement and ensure that products meet quality standards (Wang & Shu, 2023). There are a variety of process capability indexes used in manufacturing, each offering unique perspectives on process performance (Kotz & Johnson, 2002).

The basic process capability indexes include C_p, Cp_k, P_p, and Pp_k. These indexes measure the ability of a process to meet specifications and provide valuable information about process performance and potential improvement areas.

4.1.1. C_p (Process Capability)

C_p measures the potential capability of a process to meet specifications. It is calculated as the ratio of the specification width to the process width. A higher C_p value indicates a greater potential for the process to produce parts within specifications, assuming the process is stable and centred within the specification limits. C_p is particularly valuable in assessing the inherent variability of a process and its ability to meet design requirements. C_p is calculated as follows:

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

Where:
$USL = Upper\ Specification\ Limit$
$LSL = Lower\ Specification\ Limit$
$\acute{\sigma} = Sigma\ Estimator$

4.1.2. Cp_k (Process Capability Index)

Cp_k, on the other hand, is a measure of the actual capability of a process, accounting for both centring and variation. It considers the distance between the process mean and the nearest specification limit, providing a more comprehensive assessment of process performance compared to C_p. A Cp_k value greater than 1 indicates that the process is capable of meeting specifications (Žmuk, 2012). Cp_k is especially useful in determining whether a process is capable of consistently meeting customer requirements and design specifications. Cpk is calculated by taking the minimum of either Cp_U or Cp_L:

$$Cp_U = \frac{(USL - \bar{x})}{3\acute{\sigma}}$$
$$Cp_L = \frac{(\bar{x} - LSL)}{3\acute{\sigma}}$$
$$Cp_K = min(Cp_U, Cp_L)$$

or

$$Cp_k = min\left\{\frac{USL - \bar{x}}{3\acute{\sigma}}, \frac{\bar{x} - LSL}{3\acute{\sigma}}\right\}$$

Where:
$USL = Upper\ Specification\ Limit$
$LSL = Lower\ Specification\ Limit$
$Cp_U = Process\ Capability\ Index\ (Upper)$
$Cp_L = Process\ Capability\ Index\ (Lower)$

$\acute{\sigma} = Sigma\ Estimator$
$\bar{x} = Mean\ of\ Gathered\ Data$

4.1.3. P_p (Process Performance Index)

P_p measures the potential capability of a process like C_p, but it does not account for process centring. It is calculated as the ratio of the specification width to the process width, providing insights into the process's ability to meet specifications if it were perfectly centred. P_p is valuable for understanding the overall variability of a process and its potential to meet specifications, regardless of centring. Calculating P_p is similar to that of C_p calculations. However, an important distinction between the two is that P_p makes use of standard deviation whereas C_p estimates the sigma value using a moving range calculation.

$$P_p = \frac{(USL - LSL)}{6\sigma}$$

Where:
$USL = Upper\ Specification\ Limit$
$LSL = Lower\ Specification\ Limit$
$\sigma = Sigma\ Estimator$

4.1.4. Pp_k (Process Performance Index)

Pp_k, like Cp_k, is a measure of the actual capability of a process, considering both centring and variation. It provides a more comprehensive assessment of process performance compared to P_p, accounting for the process mean and variation relative to the specification limits. Pp_k is particularly useful in evaluating the long-term performance and stability of a process, as it considers both process centring and variability. Just as is the case in calculating P_p, Pp_k also makes use of standard deviations rather than sigma estimates as seen with C_p and Cpk calculations.

$$Pp_U = \frac{(USL - \bar{x})}{3\acute{\sigma}}$$
$$Pp_L = \frac{(\bar{x} - LSL)}{3\acute{\sigma}}$$
$$Pp_K = min(Pp_U, Pp_L)$$

or

$$Pp_k = min\left\{\frac{USL - \mu}{3\sigma}, \frac{\mu - LSL}{3\sigma}\right\}$$

Where:
$USL = Upper\ Specification\ Limit$
$LSL = Lower\ Specification\ Limit$
$Pp_U = Process\ Performance\ Index\ (Upper)$
$Pp_L = Process\ Performance\ Index\ (Lower)$
$\sigma = Sigma\ Estimator$
$\mu = Mean\ of\ Gathered\ Data$

4.1.5. Significance in Manufacturing

PCIs are extensively used in manufacturing to assess and enhance the capability of processes to consistently produce products within specified limits (Munro, et al., 2015). These indexes provide valuable insights into the performance and variability of manufacturing processes, allowing organisations to make informed decisions and improvements.

- Assessing Process Performance: PCIs, such asC_p, Cp_k, P_p, and Pp_k, are used to evaluate the potential and actual capability of manufacturing processes. By calculating these indexes, manufacturers can assess how well their processes perform in meeting specifications and identify areas for improvement. This assessment is crucial for ensuring that products consistently meet quality standards and customer requirements.
- Quality Improvement: Process capability analysis using PCIs is instrumental in identifying opportunities for quality improvement. By understanding the capability of manufacturing processes, organisations can implement targeted improvements to reduce variability, minimise defects, and enhance product quality (Austin, 2014). This leads to increased customer satisfaction and reduced costs associated with rework and scrap.
- Predicting Process Reliability: PCIs are used to predict the reliability of manufacturing processes in consistently producing parts within specifications. Through process capability studies, manufacturers can forecast the ability of their processes to deliver products that meet quality requirements. This predictive capability is essential for ensuring the reliability and consistency of manufacturing operations (De-Felipe & Benedito, 2017).
- Setting Product Specifications: Manufacturers use PCIs to set product specifications based on the capability of their processes. Understanding the process capability allows organisations to align product specifications with customer requirements and business needs. This ensures that products are designed within the achievable capability of the manufacturing processes, leading to improved efficiency and reduced waste.
- Driving Continuous Improvement: Process capability analysis using PCIs serves as a foundation for driving continuous improvement in manufacturing processes. By regularly assessing process capability and identifying areas for enhancement, organisations can implement targeted initiatives to improve process performance, reduce variability, and increase overall capability. This continuous improvement approach contributes to long-term competitiveness and operational excellence while driving down manufacturing possibly offering high value products at a lower cost (Žmuk, 2012).

In conclusion, process capability indexes are valuable tools in manufacturing for assessing the ability of processes to meet specifications and produce high-quality products consistently. The basic process capability indexes, including C_p, Cp_k, P_p, and Pp_k, provide insights into the potential and actual capability of manufacturing processes, enabling manufacturers to make informed decisions and improvements. Understanding and applying process capability analysis can lead to enhanced quality, reliability, and cost-effectiveness in manufacturing processes, ultimately contributing to customer satisfaction and business success.

4.2. Selecting an Appropriate PCI

The basic PCIs of C_p, Cp_k, P_p, and Pp_k, are common PCIs used in manufacturing with C_p and Cp_k being most commonly used (Žmuk, 2012). There are far more PCIs available for use in manufacturing. In his doctoral dissertation titled, Process Capability Calculations with Nonnormal Data in the Medical Device Manufacturing Industry, James Kwiecien lists many more PCIs that can be employed for use in manufacturing (Kwiecien, 2017). However, these PCIs are not common in manufacturing and will be rarely mentioned or used outside of specialised processes and monitoring requirements.

When choosing the appropriate PCI, it's important to consider whether the process is well-centred and stable. For instance, if the process is not well-centred, Cpk or Ppk would be more appropriate as they account for process centring. On the other hand, if the process is well-centred, C_p or P_p can be used to assess the potential capability of the process. It is also crucial to consider the type of data available, either short-term or long-term, and the specific requirements of the process.

For example, short-term data is measured over a short time period and represents the variation at a certain time, while long-term data provides a more comprehensive view of process variation over a longer period.

Several academic studies have investigated the use of process capability indices. One notable study is "Understanding Process Capability Indices" by Stefan Steiner, Bovas Abraham, and Jock MacKay from the University of Waterloo. This study provides a comprehensive understanding of process capability indices and offers guidelines for their appropriate use (Steiner, et al., 2000).

Another significant resource is a bibliography of the literature on process capability indices for the period 2000–2009, which contains approximately 530 journal papers and books on the subject (Bong-Jin & Kwan-Woo, 2011). Additionally, a study titled "Capability performance analysis for processes with multiple..." discusses the use of process capability indices in the manufacturing industry to provide numerical measures for process potential (Tsang-Chuan, et al., 2013). Furthermore, "Assessing process capability based on the lower confidence bound" is a study that delves into the efficiency of process capability indices as measures of process capability from various perspectives (Chang & Chien-Wei, 2008). These studies offer valuable insights into the use and implications of process capability indices in manufacturing and provide a rich source of academic literature on the topic.

The aim of this research is to develop a cost-effective I4.0 solution while considering the skills gap in UK manufacturing. To achieve this, the selection of an appropriate PCI for use in a CNC machining centre is crucial. The following criteria should be considered when choosing a PCI:

- Must be a common PCI currently used in manufacturing environments.
- Must not be overly complex, making it easily understood by operators with little or no statistical training.
- Must be capable of performing calculations by a Numerical Control Unit (NCU) without the need for external computing power or equipment.
- Must be resilient enough to handle continuous data input and react to changes.

When considering PCIs, it is important to prioritise those that align with these criteria to ensure the effectiveness and accessibility of the I4.0 solution in the manufacturing environment.

4.3. Conclusion

The use of Pp_k would be the best choice for a PCI in a close-loop CNC based on the specific criteria and requirements outlined above. The Pp_k index is a measure of the actual capability of a process, considering both centring and variation, and it is particularly useful in evaluating the long-term performance and stability of a process, as it considers both process centring and variability (Steiner, et al., 2000). This aligns with the need for a PCI that is resilient enough to handle continuous data input and react to changes, as stated in the criteria for choosing a PCI for use in a CNC machining centre.

The Pp_k index is also capable of performing calculations by a Numerical Control Unit (NCU) without the need for external computing power or equipment, which is another important criterion. Additionally, Pp_k provides valuable insights into the process's ability to meet specifications, regardless of centring, and is used to predict the reliability of manufacturing processes in consistently producing parts within specifications. This predictive capability is essential for ensuring the reliability and consistency of manufacturing operations, which is crucial for the effectiveness of an I4.0 solution in the manufacturing environment.

Furthermore, the Pp_k index is commonly used in manufacturing environments, and, like the other process capability indexes, it is instrumental in identifying opportunities for quality improvement, setting product specifications, and driving continuous improvement in manufacturing processes.

With Ppk being common, there will be little need to retrain engineers and operators on additional PCIs although this does not eliminate the need for wider adoption of six sigma within manufacturing (Kwiecien, 2017). The selection of an appropriate PCI for use in a CNC machining centre is crucial, and it is important to prioritise those that align with the specific criteria to ensure the effectiveness and accessibility of the I4.0 solution in the manufacturing environment. The Pp_k index meets these criteria and is well-suited for assessing the capability of processes in a close-loop CNC environment.

The information provided in the academic literature supports the use of process capability indexes, including Pp_k, in manufacturing environments to assess and enhance the capability of processes to consistently produce products within specified limits. One such study also made use of a touch trigger probe mounted inside a CNC machining centre (Austin, 2014). However, this study made use of Pp_k rather than Pp_k. Using Pp_k would have made Austins work more resilient should the process become unstable resulting in the Cp_k being overestimating the capability (Steiner, et al., 2000). The specific criteria outlined for choosing a PCI for use in a CNC machining centre align with the capabilities of the Pp_k index, making it the best choice for this application.

5. CNC Controller Functionality and Accuracy

5.1. CNC Controllers and G-Code

5.1.1. CNC Controller

CNC controllers, also known as CNC control units (NCUs), are integral to the operation of CNC machines, as they translate digital instructions into precise physical movements. They perform key functions such as G-code interpretation, kinematic control, spindle control, tool changer control. As technology advances, CNC controllers are becoming more sophisticated, offering greater precision, flexibility, and connectivity (Yusof & Latif, 2015). They also enhance user-friendliness through features like conversational programming and program simulation. Research has shown the development of open CNC controller systems, modelling of real-time properties of open architecture CNC systems, and the use of CNC controllers to improve the motion accuracy of industrial robots (Miller & Loucks, 1996). Additionally, innovative approaches, such as using Raspberry Pi and cloud computing for a dependable CNC controller and employing CNC controllers to control autonomous seedling planting robots, demonstrate the diverse applications and advancements in CNC controller technology.

The development of open CNC controller systems has been a popular topic in the last three decades due to the exclusivity and cost of current CNC systems (Hatem, et al., 2020). Research has proposed a novel modelling method for specifying open architecture CNC systems, providing full support for specifying hard real-time property and feedback characteristics needed for modelling these systems (Tiammiao, 2011). Furthermore, the application of industrial robots in machining has led to the proposal of using CNC systems to improve motion accuracy, with experimental analysis demonstrating the benefits of CNC systems in achieving better path accuracy and stability (Wu & Kuhlenkoetter, 2022).

In addition to these advancements, innovative approaches have been explored, such as the use of Raspberry Pi and cloud computing to create a dependable CNC controller, which aims to improve the performance and reliability of CNC machines (Osman, et al., 2022). Furthermore, the idea of using a closed-loop control system of CNC machines to control an autonomous seedling planting robot has been proposed, highlighting the diverse applications of CNC controllers beyond traditional machining processes (Rafiee & Sorouri, 2023).

These academic references support the claims made about the pivotal role of CNC controllers in modern manufacturing and their evolving sophistication, as well as their diverse applications and technological advancements. The use of CNC machines is a key technology in manufacturing and forms a solid base for automation (Yusof & Latif, 2015).

5.1.2. G-Code Programming

G-code programming, the language of CNC machines, has revolutionised manufacturing processes, enabling the production of intricate and complex components with remarkable precision and efficiency (Latif, et al., 2021). It consists of a series of alphanumeric codes that tell the machine where to move, how fast to move, and what path to follow. G-code translates the design into instructions the machine can understand (Rahman, et al., 2023). G-code controls the CNC machine by providing specific instructions for each step of the machining process. It dictates the tool's movement along the X, Y, and Z axes, as well as other parameters such as spindle speed, feed rate, and tool changes. The machine reads and executes these instructions to precisely shape the workpiece according to the design (Zhang, et al., 2023).

There are various methods for programming G-code in CNC machines, including manual programming, computer-aided programming, and conversational programming. Manual programming involves writing G-code directly, while computer-aided programming uses software to generate G-code from a CAD model. Conversational programming allows operators to input parameters using a simple interface, which the system then converts to G-code (Nguyen, et al., 2020).

While G-code programming offers numerous advantages, it also presents certain challenges and limitations. Programming can be complex and challenging to learn, requiring a thorough understanding of CNC machine operation, coordinate systems, and geometric principles. This learning curve can limit the accessibility of G-code programming to certain individuals and the complexity and size of the programs grow with the complexity of the required geometry. Errors in G-code programs can lead to costly machine damage, material waste, and production delays. Debugging G-code programs can be time-consuming and will eventually require some runtime on a CNC. Even a well-constructed G-code program with no errors can still cause damage. This is due to the nature of G-code being used to guide a cutting tool, but it does not guarantee correct cutting parameters or methods if the programmer has no metal cutting experience. Even with automated execution such as the use of CAM software, human error can still occur during the programming and setup phases, leading to incorrect tool selection, improper parameter settings, or faulty machine configurations.

G-code programming can also be restrictive and by itself, not allowing for any variation in the working environment (Xu & Newman, 2006). The inclusion of Macro B programming adds flexibility to G-code programs.

5.1.3. Macro B Programming

Macro B programming offers a great deal of flexibility to CNC programming. While traditional G-code programming relies on hard coded figures, Macro B programming instead uses variables preceded with the hash icon e.g., #100 (Hasan, 2016). These hash variables contain numerical values that can be set but the operator/programmer or can be the result of a calculation designed to determine optimum cutting conditions or toolpath positions (Hasan, 2016). Using hash variable gives a G-code program flexibility and adaptability while also aiding in reducing programming times thanks to the ability to use logic loops to create cutting cycles in part due to it similarity to other, high-level programming languages (Omirou, 2016).

Macro B programming in CNC machining is a powerful tool that enables the creation of custom commands and streamlines repetitive tasks, ultimately reducing the amount of code needed and simplifying complex operations which will ultimately improve production efficiencies

(Djassemi, 2000). This capability is particularly beneficial for the adaptation of a single program to different machines and parts, leading to increased productivity and cost savings. Additionally, macro programming facilitates the automation of specific tasks, such as gear generation and chamfer milling, thereby optimising CNC machining processes (Rodriguez-Alabanda, et al., 2019).

The use of touch trigger probes in conjunction with Macro B programming further enhances the efficiency and accuracy of CNC machining (Austin, 2014). Touch trigger probes are used for workpiece set-up, tool setting, and inspection, and when integrated with Macro B programming, they enable seamless automation of these tasks within the machining process (Hasan, 2015). This integration contributes to improved precision, reduced set-up times, and enhanced overall productivity.

5.2. Methodology

Process capability index (Pp_k) is a crucial metric in statistical process control (SPC), employed to assess the ability of a manufacturing process to produce parts within specified tolerance limits (Munro, et al., 2015). NCUs play a pivotal role in CNC machining, and their ability to accurately calculate Pp_k values is essential for ensuring process stability and product quality. This study aims to systematically evaluate the Ppk value calculation capability of NCUs using a structured testing methodology.

To assess the NCU's ability to calculate Ppk values effectively, a G-code program will be developed utilising Macro B programming methods. The #800 range of variables will be employed, as this range is currently unused on the CNC available for testing and will store data if the machine loses power (Hasan, 2015). Rewriting existing hash variable numbers will be a critical feature for the accurate and ongoing measurement of Pp_k during production. To comprehensively evaluate the NCU's capabilities, multiple data sets will be employed.

Within each of the three test groups, three distinct data sets will be generated (Appendix 10.1). Each test group will yield a progressively higher resulting Pp_k value. This approach serves to ensure that the NCU can still calculate Pp_k values when the mean and standard deviations become small and to verify that data rounding does not significantly impact the overall accuracy of the result. Each data set will comprise a sample size of 30 individual data points, all falling within a fictional tolerance range of 13.75 and 14.25.

The G-code program will be executed on the CNC machine, and the resulting data points will be extracted and analysed. The Pp_k value for each data set will be calculated and compared to the expected value. This process will be repeated for all three data sets within each test group, providing a comprehensive assessment of the NCU's ability to calculate Pp_k values for a range of mean and standard deviation values.

Expected outcomes are:

- The NCU should accurately calculate Ppk values for all three data sets within each test group.
- The NCU should demonstrate consistent performance in calculating Ppk values, regardless of the mean and standard deviation of the data.
- Rounding of data should not significantly impact the overall accuracy of the Ppk value calculation.
- The NCU will be able to rewrite the hash variables when required.

By employing a structured testing methodology, this study will provide a comprehensive evaluation of the NCU's ability to calculate Ppk values accurately and consistently.

The resulting Ppk calculations and results for each data set is as follows:

	Range:13.80 – 14.20 Pp_k<1.0			Range:13.90 – 14.10 Pp_k<1.5			Range:13.95 – 14.05 Pp_k>1.5		
	Data Set 1	Data Set 2	Data Set 3	Data Set 4	Data Set 5	Data Set 6	Data Set 7	Data Set 8	Data Set 9
LSL #801	13.75	13.75	13.75	13.75	13.75	13.75	13.75	13.75	13.75
USL #802	14.25	14.25	14.25	14.25	14.25	14.25	14.25	14.25	14.25
Mean #804	13.978	14.014	13.992	13.996	13.988	13.996	13.994	14.003	14.005
Std Dev #807	0.107	0.100	0.113	0.058	0.058	0.060	0.029	0.028	0.028
Pp_k #800	0.709	0.787	0.712	1.412	1.379	1.357	2.796	2.968	2.929

Figure 4 - Expected Results from Appendix 10.1 Data

5.3. Results

The systematic evaluation of the NCU ability to calculate Pp_k values using a structured testing methodology has yielded positive and successful outcomes. The study aimed to assess the NCU's proficiency in calculating Pp_k values under varying conditions, including different mean and standard deviation values.

5.3.1. Accuracy of Ppk Calculation

The evaluation of the NCU ability to calculate Pp_k values displayed a consistent level of accuracy across all testing scenarios. In each of the three test groups, the NCU consistently produced Pp_k values that aligned closely with the expected values. Notably, as the mean and standard deviations approached minimal values, the NCU maintained its precision, highlighting its capability to handle data distributions with a high degree of accuracy. This accuracy is pivotal for ensuring that the manufacturing process consistently produces parts within the specified tolerance limits.

5.3.2. Consistency in Performance

The NCU demonstrated a high level of consistency in its performance throughout the testing process. Despite variations in mean and standard deviation values introduced deliberately within each test group, the NCU consistently generated dependable Pp_k values. This consistency is a key attribute for effective statistical process control in CNC machining, as it ensures that the NCU's calculations remain dependable under diverse operating conditions. The ability to maintain performance consistency is vital for achieving and sustaining high levels of product quality. There was also no discernible difference in the time taken to calculate each dataset.

5.3.3. Impact of Data Rounding

A crucial element of the investigation involved assessing the potential impact of data rounding on the overall accuracy of Pp_k calculations. The findings indicate that the NCU demonstrated resilience in the presence of data rounding, with minimal effects on the precision of Ppk values. It is noteworthy that the NCU's adaptability to real-world manufacturing scenarios, where rounding may occur during CNC machining operations, was evident. The NCU's capability to manage rounded data underscores its robust performance in practical manufacturing environments.

It's important to note that while the calculations remained largely unaffected by rounding, some rounded values were displayed for visualisation purposes. This practice ensures transparency in reporting and aids in the interpretation of results, allowing for a comprehensive understanding of the NCU's performance under varied conditions

5.3.4. Hash Variable Rewriting Capability

The study assessed the NCU's critical capability to rewrite hash variables, a feature essential for the accurate and ongoing measurement of Ppk during production. The NCU demonstrated proficiency in rewriting hash variables when required, highlighting its adaptability to evolving manufacturing processes. This capability ensures that the NCU can seamlessly integrate with changes in CNC machining operations, maintaining accurate Ppk calculations and contributing to the long-term stability of the manufacturing process.

5.4. Conclusion

The results of the structured testing methodology provide a comprehensive and positive assessment of the NCU's ability to calculate Pp_k values accurately and consistently. The combination of high accuracy, performance consistency, resilience to data rounding, and hash variable rewriting capability positions the NCU as a robust tool for statistical process control in CNC machining. These successful outcomes validate the NCU's effectiveness in maintaining process stability and upholding stringent quality standards in manufacturing processes. The findings instil confidence in the NCU as a reliable component for ensuring the precision and reliability of CNC machining operations.

The concern regarding the number of hash variables required for Pp_k calculations in a closed-loop CNC manufacturing process is a critical consideration in the quest for process optimisation. The utilisation of 70 individual variables from #800 to #869 for these calculations, while not inherently problematic, can pose challenges when Pp_k is needed for multiple features on the same part. For instance, measuring the length and width of a simple block would necessitate 140 separate variables, potentially leading to management complexities and operational inefficiencies.
While it is feasible to perform the Pp_k calculation using fewer variables, this approach may introduce programmatic complexities and impede operators and programmers in the debugging process. An alternative proposition involves decreasing the sample size from 30 to 15, a strategy supported by research indicating that a sample size of 15 or below more accurately reflects the variability of a given process (Ali, et al., 2008). This reduction not only alleviates the strain on available variables within the NCU but also enhances the precision of process condition recording.
The seamless integration of closed-loop CNC manufacturing, coupled with prudent variable management strategies, is pivotal in the pursuit of operational excellence and process optimisation. By addressing concerns related to variable utilisation and sample size, manufacturers can fortify their manufacturing processes, minimise operational complexities, and elevate the accuracy and efficiency of their production operations.

6. CNC Machine Measurement Ability

6.1. Assessing Measurement Ability

The measurement ability of a CNC machine is important for several reasons (Kwon, et al., 2006). First, it allows manufacturers to ensure that their products are being produced to the desired specifications. Second, it can help to identify and correct problems in the manufacturing process. Third, it can be used to improve the efficiency and accuracy of the manufacturing process (Burdick, et al., 2003).

One of the key factors that affects the measurement ability of a CNC machine is repeatability (Blecha, et al., 2022). Repeatability is the ability of the machine to produce the same measurement result multiple times when measuring the same part. If the repeatability of the CNC machine is poor, then it can be difficult to distinguish between real variation in the process and that of the measurement system. This can lead to incorrect conclusions about the process and undermine any confidence in a closed loop system (Al-Qudah, 2017). Poor repeatability can also lead to increased costs due to scrap, rework, and inspection. If the CNC machine is not able to produce accurate measurements, then it is more likely that parts will be produced that do not meet specifications. This can lead to scrap, rework, and additional inspection costs (Tseng, et al., 2005).

Another factor that affects the measurement ability of a CNC machine is reproducibility. Reproducibility is the ability of different operators to produce the same measurement result when measuring the same part. If the reproducibility of the CNC machine is poor, then it can be difficult to ensure that all parts are being measured accurately.
To determine the performance of a CNC machine's measurement system, gauge repeatability and reproducibility (R&R) testing is used. Gauge R&R testing measures the variability of a measurement system and identifies the sources of that variability. This information can then be used to improve the accuracy and reliability of the measurement system.

6.1.1. Type 1 Gauge R&R testing

Type 1 gauge R&R testing is used to determine the amount of variation in a measurement system that is due to the repeatability of a single operator. This testing is conducted by having a single operator measure the same part multiple times. The variability of the measurements is then used to calculate the repeatability of the measurement system. Results below 10% considers the system to be capable. Should a measurement system score above 30% it should not be used in its current state and efforts should be undertaken to reduce variation (Al-Qudah, 2017). Results between 10% and 30% are acceptable and the measurement system can be used. however, this would need to be agreed upon with either the customer or senior figures within a company before doing so (Urdhwareshe, 2006). Type 1 gauge R&R testing is a valuable tool for assessing the measurement ability of CNC machines. By conducting regular Type 1 gauge R&R testing, manufacturers can identify and address potential problems with their measurement systems before they cause quality problems.

6.1.2. Benefits of assessing the measurement ability of a CNC

There are several benefits to assessing the measurement ability of a CNC machine. These benefits include:

- Improved product quality: By ensuring that the CNC machine can produce accurate measurements, manufacturers can produce products that meet customer specifications (Burdick, et al., 2003).
- Reduced costs: By identifying and addressing potential problems with the measurement system, manufacturers can reduce the costs associated with scrap, rework, and inspection.
- Increased efficiency: By using a reliable and consistent measurement system, manufacturers can improve the efficiency of their manufacturing process.
- Improved confidence: By having confidence in the measurement system, manufacturers can have greater confidence in their closed loop system and the quality of their products (Tseng, et al., 2005).

6.1.3. Conclusion

Assessing the measurement ability of a CNC machine is an important part of ensuring quality and efficiency in the manufacturing process (Holub, et al., 2018). By conducting regular Type 1 gauge R&R testing, manufacturers can identify and address potential problems with their measurement systems before they cause quality problems. This can lead to improved product quality, reduced costs, increased efficiency, and improved confidence in the manufacturing process (Žmuk, 2012).

Additional benefits of assessing the measurement ability of a CNC:

- Improved customer satisfaction: By producing products that meet customer specifications, manufacturers can improve customer satisfaction.
- Reduced warranty costs: By reducing the number of products that do not meet specifications, manufacturers can reduce warranty costs.
- Increased market share: By producing high-quality products, manufacturers can increase their market share.
- Enhanced brand reputation: By demonstrating a commitment to quality, manufacturers can enhance their brand reputation.
- Overall, assessing the measurement ability of a CNC machine is a valuable investment that can lead to several benefits for manufacturers.

6.2. Methodology

To determine the measurement ability of a CNC (Kwon, et al., 2006), three different groups of thirty ø19mm Acetyl Copolymer test pieces will be used as inspection articles.

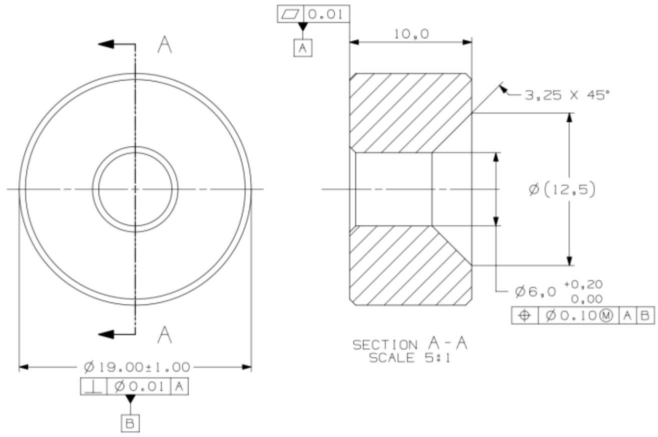

Figure 5 - Drawing of Test Pieces

Each of the three groups will have a different Pp_k values resulting in less deviation between the individual test pieces within a given group. Each test piece has been measured using a Mitutoyo CMM that has been calibrated and approved for production use and the resulting Pp_k values of each group are as follows:

Group	Effective Tolerance Band (mm)	Mean	Standard Deviation	Pp_k
Black	2.0	18.9697	0.3626551	0.891554
Blue	2.0	19.01327	0.247922	1.326673
White	2.0	18.983	0.187064	1.751626

Figure 6 - Capability Data for Test Piece Groups

Two tests will be conducted using these test pieces:

- Type 1 Gauge R&R on randomly selected pieces from each of the three groups
- Bland-Altman Analysis on each of the thirty test pieces from each of the three groups

Each test will make use of Renishaw's probing macro O9019. This macro program measures the diameter and position of a bore or boss. This result can then be used to update cutting tool offsets or used to set a workpiece datum prior to machining. O9019 takes four measurement points, 2 in the Y axis and another two in the X axis (Renishaw plc, 1996). The macro program then finds a best fit to a given diameter based off the data gathered.

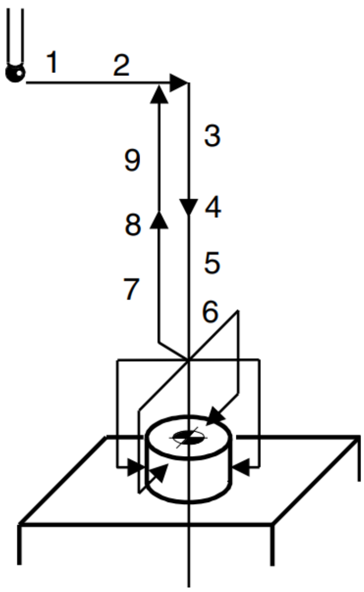

Figure 7 - Probe Movements When Measuring (Renishaw plc, 1996)

To protect the touch probe and the CNC machine, another of Renishaw's macro programs will be used, O9014. This program enabled protected positioning when using the probe and halts the machine if contact is made with the probe during its movements to a given position (Renishaw plc, 1996).

6.2.1.Type 1 Gauge R&R

For the Type 1 Gauge R&R analysis, a meticulous evaluation will be conducted on a randomly selected part from each defined group. This comprehensive examination aims to assess the reliability and consistency of the CNC measurement system by subjecting an individual test piece to repeated measurements. Specifically, the chosen parts will undergo 30 measurements, enabling a robust statistical evaluation of its repeatability.

The measurement process will employ Renishaw's probing macro O9019, ensuring precise determination of the diameter and position of the specified features on the test pieces. These measurements will be conducted under controlled conditions to mimic real-world production scenarios. The obtained data will be subjected to standard Type 1 calculations, including the calculation of repeatability and reproducibility components, to derive the Precision to Tolerance (P/T) ratio (Urdhwareshe, 2006). This ratio will serve as a crucial indicator of the CNC's capability to consistently produce measurements within specified tolerances.

The results of the Type 1 Gauge R&R analysis will be instrumental in gauging the CNC's reliability in a controlled setting, providing insights into its precision, repeatability, and overall suitability for industrial applications (Blecha, et al., 2022).

6.2.2.Bland-Altman Analysis

For the Bland-Altman Analysis, all thirty test pieces from each group will undergo a systematic measurement process arranged in a 6 by 5 array. This structured layout is designed to capture a comprehensive dataset, as each test piece will be measured multiple times in a grid pattern. This approach ensures a thorough exploration of the CNC's measurement performance, capturing potential variations in different spatial dimensions.

To enhance the robustness of the analysis, this measurement arrangement will be repeated three times for each group, yielding a rich set of data for subsequent comparison. The Bland-

Altman method will be employed to assess the agreement between the measurements obtained from the CNC and the reference measurements acquired from the calibrated Mitutoyo CMM (Kwon, et al., 2006). The resulting Bland-Altman plots will depict any systematic bias or limits of agreement between the two measurement methods (Mansournia, et al., 2021).

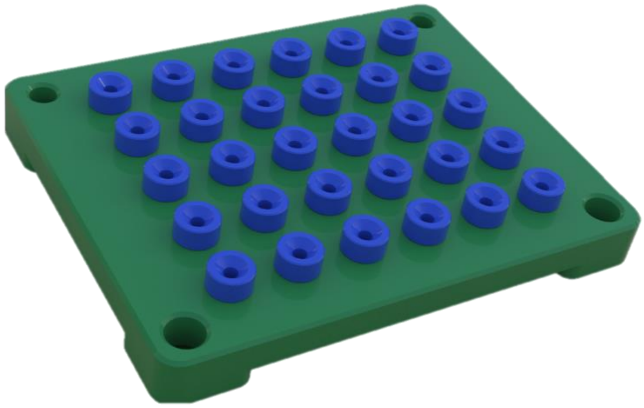

Figure 8 - Render of BLUE Group Test Parts in 6 x 5 Array

This multi-faceted approach, combining repeated measurements and the Bland-Altman method, aims to uncover subtle nuances in the CNC's measurement behaviour, providing a comprehensive understanding of its accuracy and agreement with established measurement standards (Giavarina, 2015). The comparison with the CMM data will serve as a crucial benchmark, affirming the CNC's reliability for industrial metrology applications (Tseng, et al., 2005).

6.2.3.Expected Outcomes

The anticipated outcomes of the Type 1 Gauge R&R and Bland-Altman analyses are poised to provide valuable insights into the performance characteristics of the CNC measurement system. These analyses, designed with meticulous consideration of statistical rigor and real-world applicability, are expected to yield the following outcomes:

Type 1 Gauge R&R Analysis:

- Repeatability and Reproducibility Assessment: The meticulous examination of three randomly selected parts from each group, involving 30 repeated measurements per part, is expected to reveal a comprehensive understanding of the CNC's repeatability and reproducibility. The Precision to Tolerance (P/T) ratio, derived from standard Type 1 calculations, will serve as a pivotal indicator of the CNC's ability to consistently generate measurements within specified tolerances.
- Insights into Reliability: The outcomes of the Type 1 Gauge R&R analysis will offer insights into the CNC's reliability in controlled settings. Precision and repeatability metrics will be crucial in determining the system's robustness, paving the way for informed decisions regarding its suitability for the intended closed-loop system.
- Benchmarking for Industrial Applicability: The results will establish a benchmark for the CNC's precision, aiding in the assessment of its suitability for industrial metrology applications. The findings will contribute to the enhancement of quality control processes in manufacturing environments.

Bland-Altman Analysis:

- Spatial Dimension Exploration: The systematic measurement process, organised in a 6 by 5 array and repeated three times for each group, is expected to capture a comprehensive dataset. This approach will enable a thorough exploration of the CNC's measurement performance, unveiling potential variations in different spatial dimensions.
- Agreement Assessment: The application of the Bland-Altman method will facilitate a nuanced assessment of the agreement between CNC measurements and reference measurements from the calibrated Mitutoyo CMM. Bland-Altman plots will be instrumental in depicting any systematic bias or limits of agreement, providing a clear picture of the CNC's accuracy.
- Comprehensive Understanding: The multi-faceted approach, combining repeated measurements and the Bland-Altman method, aims to uncover subtle nuances in the CNC's measurement behaviour. The comparison with CMM data will contribute to a comprehensive understanding of the CNC's accuracy and alignment with established measurement standards.

In summary, the expected outcomes from these analyses will not only contribute to the scientific understanding of the CNC measurement system but will also have practical implications for its utilisation in industrial settings, enhancing precision and reliability in manufacturing processes.

6.3. Results

The testing of the CNC machine has yielded impressive results considering the age of the machinery. The precision to tolerance (P/T) ratio obtained from the Type 1 Gauge R&R analysis and the Bland-Altman Analysis has provided valuable insights into the CNC's measurement ability. However, the testing also highlighted issues with the fixturing used, which is crucial for accurate and reliable measurements. The results of the testing demonstrate the potential for the CNC machine to deliver consistent and reliable measurements within specified tolerances, while also emphasising the importance of addressing fixturing issues to further enhance its performance and suitability for industrial applications

6.3.1. Type 1 Results

The Type 1 Gauge R&R study, conducted to evaluate the reliability and consistency of the CNC measurement system, involved subjecting individual test pieces to repeated measurements. The meticulous evaluation, employing Renishaw's probing macro O9019, aimed to assess the CNC's precision and repeatability by conducting 30 measurements on each chosen part. The results of the study, including the calculation of repeatability and reproducibility components, provided a crucial indicator of the CNC's capability to consistently produce measurements within specified tolerances. The study's outcomes are instrumental in gauging the CNC's reliability in a controlled setting, offering insights into its precision, repeatability, and overall suitability for industrial applications.

The Type 1 R&R results are as follows:

Part ID	Reference Dimension (mm)	Tolerance Band (mm)	Bias (mm)	% Var Repeatability	% Var Repeatability & Bias
Black	18.360	2.0	-0.0009	0.94	1.03
Blue	19.116	2.0	-0.0007	0.96	1.04
White	19.024	2.0	0.0044	1.09	1.53

Figure 9 - Type 1 Gauge R&R Results

The results for the test pieces from both the Black and the Blue groups demonstrate consistency, with minimal bias that is consistently in the same direction, yielding slightly smaller results than the actual measurements. However, the results from the White group do not align with those from the Black and Blue groups. Despite this, all results are deemed acceptable.

The results from the Type 1 Gauge Repeatability and Reproducibility (R&R) study indicate that the measurement system is well within the acceptance criteria range of 10%. However, it is important to note that the tolerance band significantly influences the calculation of the system's variability. In this context, the study involved recalculating the measurements using decreased tolerance bands to establish the minimum tolerance that could be applied to the CNC before its performance should be questioned.

The tolerance band, which represents the acceptable range around a target value, plays a critical role in assessing the variability of the measurement system. By reducing the tolerance bands, the study aimed to determine the lowest tolerance that the CNC could accommodate without compromising its performance. This process is essential for understanding the system's capability to consistently produce measurements within specified tolerances, especially in the context of industrial applications.

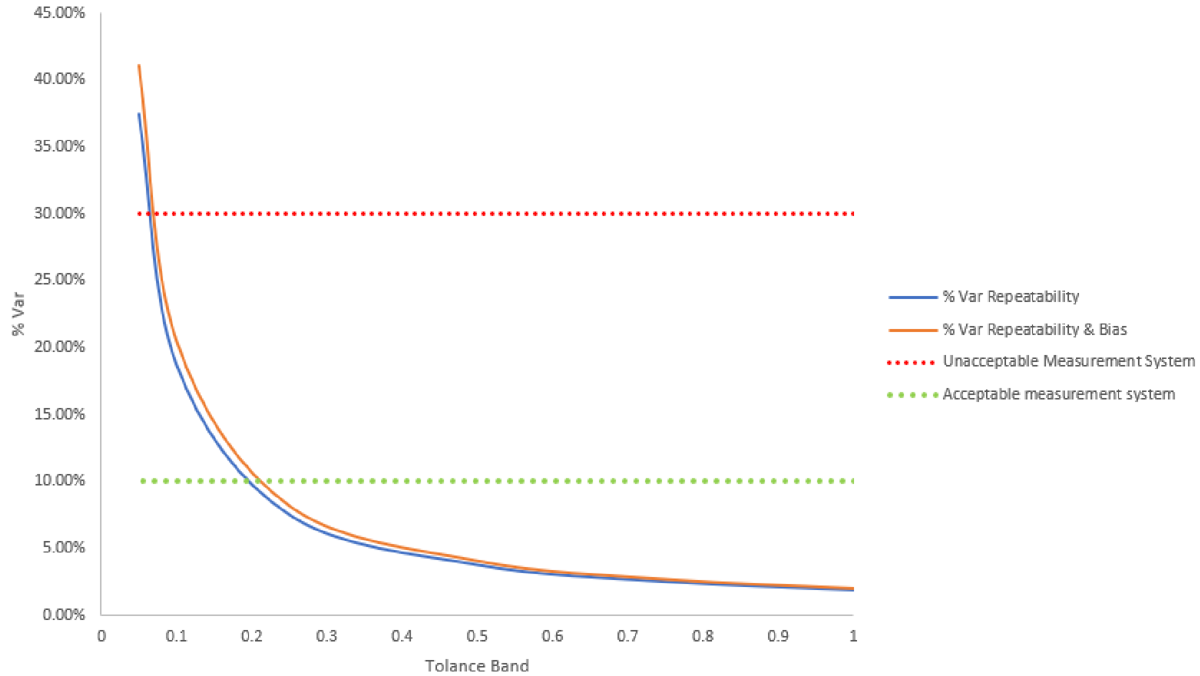

Figure 10 - R&R Results Based on Tolerance Band

The graph above shows how the CNCs measurement ability changes depending on the tolerance band being applied. A tolerance band of 0.20mm is achievable before breaking the 10% threshold, allowing the CNC to be used as an inspection tool. A tolerance band of 0.10mm is achievable if with the variability of 20% is deemed acceptable. A result between 10% and 30% is considered marginally acceptable (Urdhwareshe, 2006). While it is not intended to be used to inspect parts, the CNC would be capable of doing so with confidence and give greater confidence to the function of a closed-loop system that will rely on the performance of a touch trigger probe.

6.3.2. Bland-Altman Analysis Results

The Bland-Altman Analysis, which involved a systematic measurement process and the employment of the Bland-Altman method, aimed to uncover subtle nuances in the CNC's measurement behaviour, providing a comprehensive understanding of its accuracy and agreement with established measurement standards and equipment. However, the testing also revealed issues with the fixturing used, which are crucial for ensuring the accuracy and reliability of the measurements. These findings underscore the potential of the CNC machine to deliver consistent and reliable measurements, while also highlighting the importance of addressing fixturing issues to further enhance its performance and suitability for industrial applications.

The data collected for the Bland-Altman analysis was plotted against the measurements from the calibrated CMM to show if the results gathered by the CNC tracked.

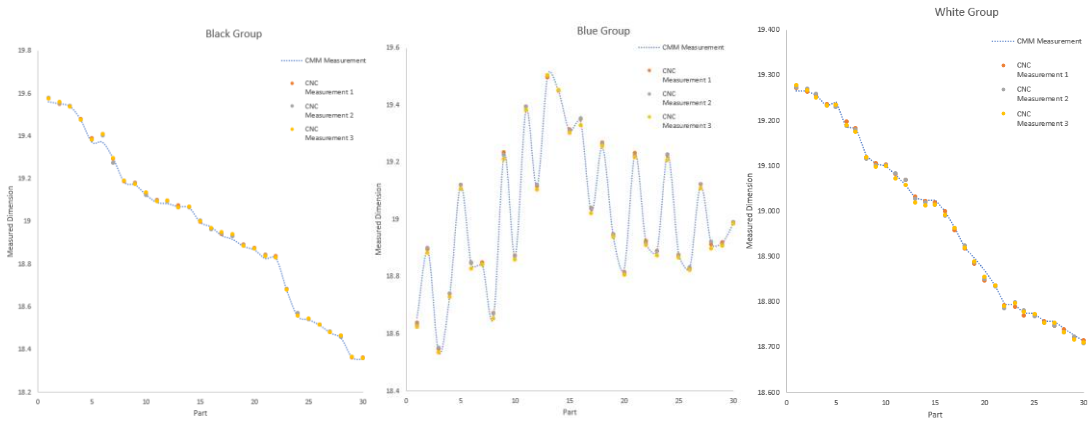

Figure 11 - Results from 6x5 Array

The graphs above shows that the measured points from the CNC track with those from the CMM. The graphs also show how the test pieces were machined to meet the required dimensions with the machinist starting at the largest required size and moving down through the tolerance band. This method was used for all three groups with part 1 being the largest of the group and part 30 being the smallest to make machining all the test parts easier and reduce waste. However, for the blue group, the parts were mixed up prior to being placed on the CNC to test the CNCs ability to react to the variability of the measurements. These results give confidence that the CNC can confidently react to differing dimensions when probing but will not show agreement with the CMM without a Bland-Altman analysis.

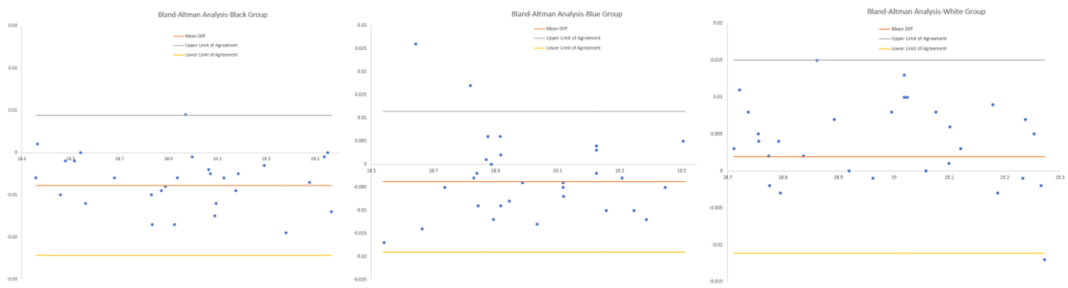

Figure 12 - Bland-Altman Analysis Results

The graphs above show the results of the Bland-Altman analysis on the gathered data. The results show that the measurement taken by the CNC and CMM are within the limits of agreement. The Bland-Altman analysis also highlights the same bias from the type 1 R&R where the data from the white group are measured larger. This could indicate that the CNC may have some difficulty in measuring when there is a small amount of variation from part-to-part but the results from the Type 1 R&R testing would show that across all three groups.

6.4. Conclusion

The testing undertaken to determine the measurement ability of a CNC machine has concluded that the machine used for testing is capable of effectively and accurately measuring test pieces within determined tolerances and that the machine is within the limits of agreement with a calibrated Mitutoyo CMM.

The data recorded shows discrepancies, particularly in the measurement of test pieces from the white group in both the Type 1 R&R and the Bland-Altman analysis, indicating a bias towards measuring parts larger than those from the other groups. This may suggest that the CNC machine faces challenges in measuring when there is minimal variation from part to part. However, a similar trend is observed in the Type 1 R&R results for the Black and Blue groups, which are closely aligned. One possible explanation for this inconsistency could be the fluctuation in ambient temperature. A significant 9°C temperature drop occurred between the time the tests were conducted on the Black and Blue groups and when the CNC was used for the white group. Despite efforts to maintain a constant temperature, the proximity of the machine to a roller shutter door had a more substantial impact than anticipated. This effect is also evident in the data obtained for the blue group during the Bland-Altman analysis. The remaining data was gathered on the same day as the white group, and the impact of ambient temperature can be seen in the Bland-Altman analysis compared to previous data gathered.

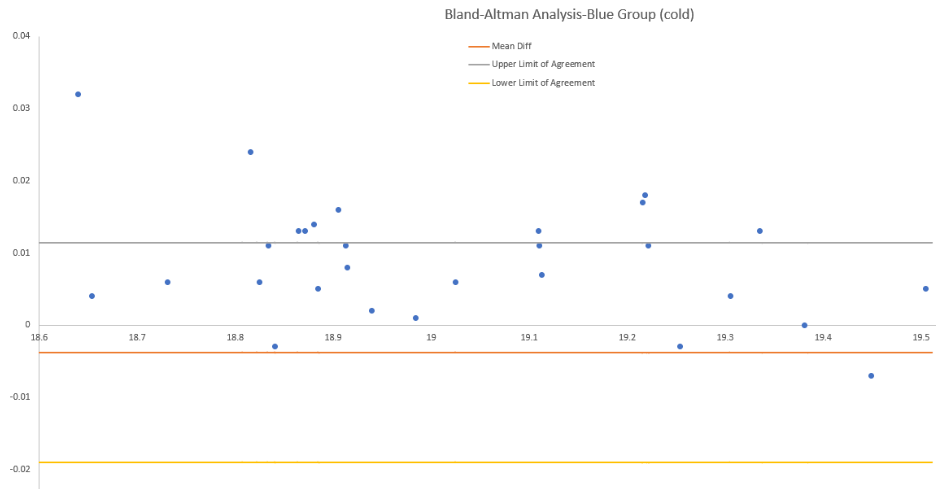

Figure 13 - WHITE Group Bland-Altman Results

The graph illustrates a significant bias towards the CNC measuring larger on a colder day for the blue group, which may help explain the observed bias in the white group. Additionally, the Bland-Altman analysis has revealed issues with the fixturing used during data collection, as the measurement points were consistently off for all three groups. Further investigation uncovered that the centre positions of the test pieces on the fixture could vary up to 0.20mm in either axis. This variation was attributed to an issue with the measurement equipment used in the tool room that manufactured the fixturing. Despite the challenges posed by fixturing and ambient temperatures, the test results have demonstrated that the specific machine is capable of accurately measuring part dimensions and providing dependable Pp_k results.

7. Automating Throughput Optimisation

7.1. Closing the Loop for Optimisation

Closed-loop CNC manufacturing, which involves the use of closed-loop systems in CNC machines, is a state-of-the-art approach that holds great potential for optimising manufacturing processes. In a closed-loop system, the CNC machine continuously receives feedback on its performance and adjusts its operations in real-time to ensure precision and accuracy (Eldessouky, et al., 2015). This contrasts with open-loop systems, where the machine operates without feedback, leading to potential errors and inefficiencies (Venkatesh, et al., 2007). A common practice of open-loop systems is to employ operators to perform inspection checks on finished parts and manually update the cutting tool offsets in the NCU before restarting the machining process. While this gives some feedback to the CNC, it depends greatly on the skill of the operator and will not necessarily reduce scrap and rework if mistakes are made or if the parts would need to be removed from the fixturing for inspection. There is also the added cost of having to employ an operator to supervise what is essentially an automated machining process.

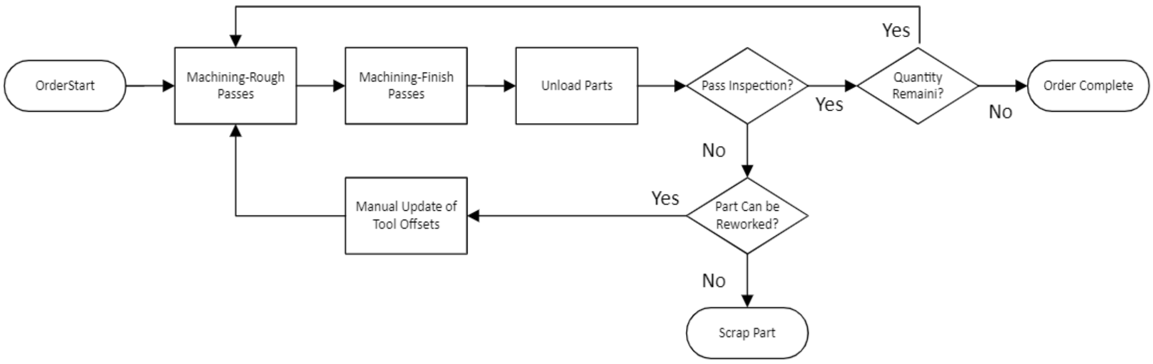

Figure 14 - Typical Process Flow with Human Feedback

The adoption of closed-loop CNC systems is driven by their ability to enhance control accuracy and improve the overall quality of machined parts (Eldessouky, et al., 2015). By continuously monitoring and adjusting the machining process, these systems can minimise errors, reduce scrap rates, and optimise production efficiency (Travez, et al., 2011). This level of precision is particularly valuable in the manufacturing of complex and intricate parts, where tight tolerances are essential. Furthermore, closed-loop CNC systems contribute to the optimisation of manufacturing processes by enabling the machine to adapt to variations in material properties and environmental conditions (Brecher, et al., 2006). This adaptive capability ensures consistent and high-quality output, even in dynamic production environments. As a result, manufacturers can achieve greater operational efficiency and cost savings while maintaining superior product quality.
The integration of probing cycles in CNC machining processes enables the establishment of a closed-loop system, which can yield a host of benefits for manufacturers (Kumar, et al., 2007). By leveraging on-machine probing, manufacturers can automate the machining process with closed-loop control, leading to improved efficiency and reduced scrap rates. This is achieved through the automatic updating of tooling offsets, which ensures that the CNC machine can adapt to variations in material properties and environmental conditions, thereby minimising errors and enhancing overall part quality. Additionally, the implementation of a semi-finishing step, which leaves a known amount of material remaining on the part, allows the CNC machine to utilise a probe to measure the part and confirm the remaining material. The probed value from the remaining material can then be used to alter the cutting tool offset without the need for human intervention (Fulkerson, 2020).

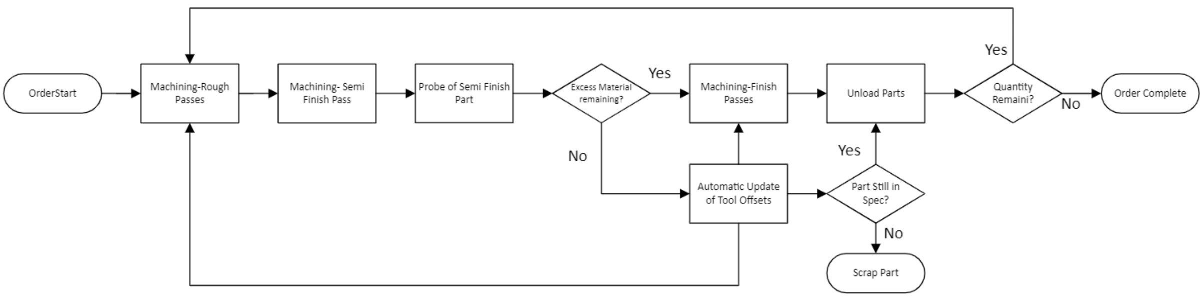

Figure 15 - Automatic Feedback using a Spindle Mount Touch Trigger Probe

This initiative-taking approach to part measurement and material confirmation contributes to the reduction of scrap and the optimisation of the manufacturing process. However, this solution does not consider the increased process capability that would result from a closed-loop system. As part variation is reduced and PCIs increase, the requirement for probing is expected to diminish. Failure to adjust the probing frequencies in line with these changes can result in lost production time due to unneeded probing cycles. Therefore, while on-machine probing and tool measurement systems are instrumental in initiative-taking defect prevention and process optimisation, it is imperative for manufacturers to dynamically adapt their probing strategies to align with the evolving process capability and part variation dynamics.

This section of the research will delve into the detailed programming logic needed to establish a state where a CNC system operates in a closed-loop configuration, integrating real-time feedback to adjust machining parameters. Furthermore, it will address the intricate process of harmonising probing frequencies with throughput, ensuring that the CNC system optimally manages the trade-off between inspection time and production throughput. This will involve the development of sophisticated control strategies to maintain an optimal balance between probing operations and overall manufacturing efficiency without the need for human intervention.

7.2. Methodology

In this section, two CNC programs will be developed to establish a closed-loop system that responds to changes in PCI values, building on the work conducted in sections 2 and 3. The first program, T121223, will incorporate positional data and sub-program calls for probing macro O9014. The second program, O1212, will encompass all probed dimensions, Pp_k and P_p calculations, and the necessary logic to set probing frequencies (Hasan, 2016). This program will be utilised as a subprogram and called by T121223 as needed. The three test groups utilised in section 3 will be employed in the same 6 by 5 arrays but will be placed in a random order. Upon completing all 30 parts from a specific test group, all macros except #801, #802, #856, #857, #858, and #859 will be reset to zero to assess the capability of O1212 to gather and process data from the beginning of a cycle and influence the actions of T121223.

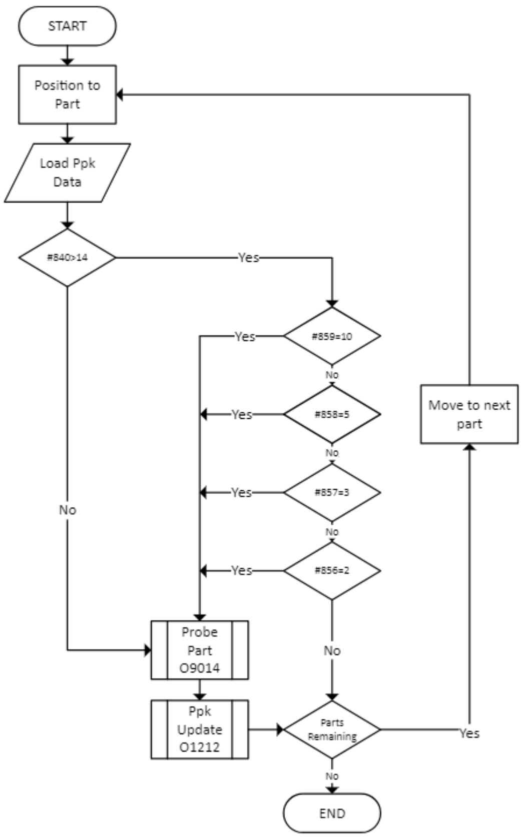

Figure 16 - Process Flow Diagram of Section 4 Testing

Once O1212 has been demonstrated to accurately gather and process data and influence the probing frequencies in T121223, the test group will be changed to one with a lower resulting Pp_k without resetting any variables in O1212. Subsequently, T121223 will be rerun with the objective of overwriting data and revising the calculated Pp_k and P_p. This methodology is aligned with the research on closed-loop CNC machining and inspection, which emphasises the integration of measuring technology and the preservation of results in the manufacturing process (Brecher, et al., 2006) (Eldessouky, et al., 2015).

The proposed methodology also aligns with the concept of closed-loop manufacturing, which involves the use of feedback from a Computer Numerical Control (CNC) to the Enterprise Resource Planning (ERP) to optimise the manufacturing process (Venkatesh, et al., 2007). Additionally, it is consistent with the development of closed-loop inspection models for the implementation of an integrated CAD/CAPP/CAIP/CAM/CAI system based on the STEP-NC standard, aiming to integrate inspection results and generate changes in operating parameters (Saif & Yusof, 2019)

7.2.1. Expected Outcomes

The expected outcome of the development and implementation of the two CNC programs to establish a closed-loop system that responds to changes in PCI values is twofold. First, it is anticipated that the integration of the T121223 and O1212 programs will enable the CNC system to dynamically adjust probing frequencies based on the gathered data after 15 parts, thereby enhancing the system's ability to maintain optimal probing strategies and production throughput. This will result in reduced use of the probe and reduced cycle times for higher Pp_k values. This aligns with the research on closed-loop CNC machining and inspection, which emphasises the integration of measuring technology and the preservation of results in the manufacturing process. The threshold for triggering different probing frequencies are as follows:

Minimum Pp_k	Maximum Pp_k	Frequency of Probe use (probe used : number of parts)
-	1.1	Every part (1:1)
1.1	1.2	Every other part (1:2)
1.2	1.5	Every 3rd part (1:3)
1.5	1.8	Every 5th part (1:5)
1.8	-	Every 10th part (1:10)

Figure 17 - Probing Frequency Intervals

Second, it is expected that the closed-loop system will demonstrate improved adaptability to variations in material properties and part characteristics, leading to a reduction in scrap rates and an optimisation of the manufacturing process should this research be used in a production environment. Additionally, the system's ability to influence the actions of T121223 based on the data gathered and processed by O1212 is expected to contribute to greater operational efficiency and cost savings while maintaining superior product quality. This will be confirmed by differences in the recorded cycle times. The difference in cycle times between the three groups should be as follows:

- BLACK Group: No change in cycle times due to Pp_k being below 1.1. Probing frequency will be every part (1:1).
- BLUE Group: Cycle time reduction after the 15th part is probed due to Pp_k being above 1.2. Probing frequency will be every other part (1:2).
- WHITE Group: Massive cycle time reduction after the 15th Part due to Pp_k being above 1.75. Probing frequency will be one part in 5 (1:5).

In summary, the expected outcome of this endeavour is the successful establishment of a closed-loop CNC system that not only reacts to changes in PCI values but also contributes to the reduction of scrap, optimisation of the manufacturing process, and maintenance of superior product quality, in line with established principles and practices in the field.

7.3. Results

The result from the above methodology is as follows:

Group ID	Group Pp_k	Resulting Pp_k from Testing	Probed Positions (of 30)	Cycle Time (minutes)
BLACK	0.8916	0.8935	30/30	40
BLUE	1.3267	1.3183	22/30	29
WHITE	1.7516	1.8059	17/30	23

Figure 18 - Results from Section 4 Testing

When running program T121223, variations in the cycle times were observed in both the BLUE and WHITE groups. This is due to the data being collected by the touch trigger probe and the calculations performed by O1212 allowed T121223 to react to the changes in the Pp_k data of the test parts in the groups used. There was no change to the cycle times when using the BLUE group of test parts. This was to be expected as the Pp_k from this group of test parts would not exceed the minimum of 1.1 required to trigger a reduction in probing frequencies.

The WHITE group saw the largest cycle time reduction. After the first round of Pp_k calculations were performed after part 15, the resulting Pp_k value was 1.7137. The settings within O1212 then set the appropriate variables so that T121223 would not probe for another five parts, or part 20 in the array. This second round of calculations would then be made up of data from positions 2 through to 15, and position 20. This resulted in a Pp_k result of 1.7289. This value again prompted T121223 to not probe again for another five parts. The third round of calculations were made up from positions 3 to 15, position 20, and position 25. The resulting Pp_k from this round of calculations was 1.805. This increase placed the probing requirement at 1:10 and with there only being five test parts remaining, T121223 skipped to the end of the program and the cycle ended.

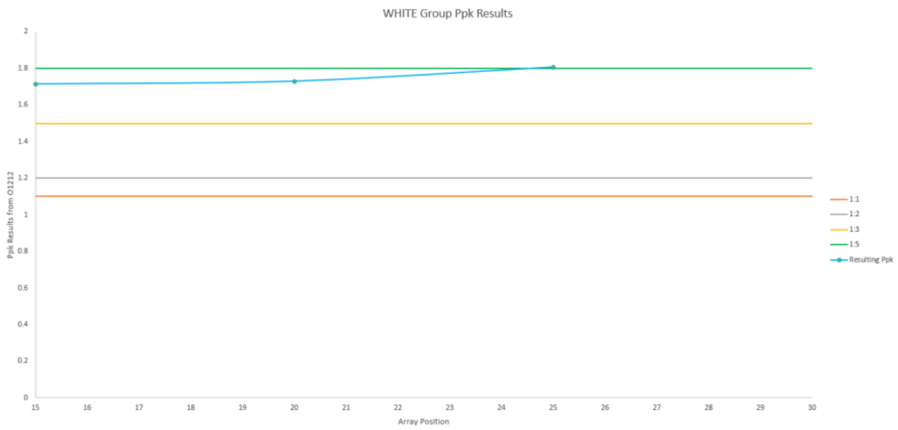

Figure 19 - WHITE Group Test Results

The BLUE group also saw a reduction is cycle time. After the first 15 positions were probed and the Pp_k calculated, the probing frequency was set to 1:2 thanks to a Pp_k 1.244. The next position in the array to be probed was position 17. The resulting Pp_k from the probing data was then 1.454. This almost triggered a probing frequency of 1:3 and has given a higher Pp_k value than the entire group when calculated together. However, the probing frequency remains at 1:2 and does so for the entire group with the final position probed being 29.

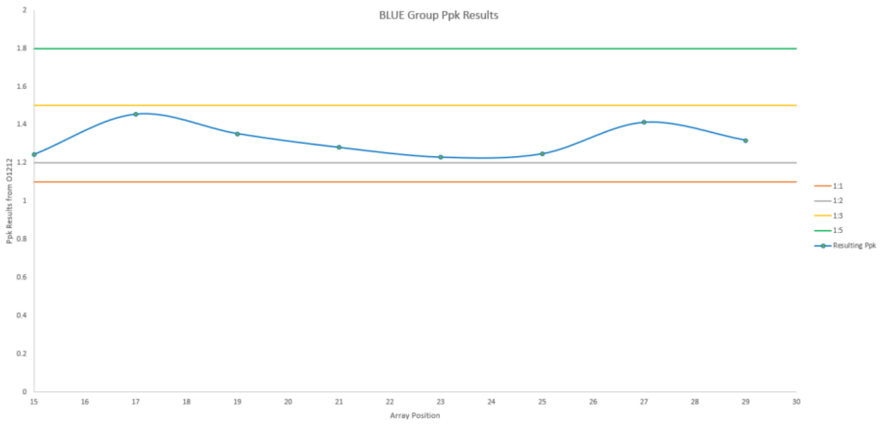

Figure 20 - BLUE Group Test Results

Once T121223 had completed its cycle for the BLUE group, the test parts were swapped for those from the BLACK group. No hash variable was reset, and the cycle restarted. This test was to not only ensure that the variables and values previously calculated by O1212 still functioned, but also to ensure that a drop in Pp_k values can be detected and accounted for. The first position on the array to be probed was position 2 due to the carry over setting of probing 1:2. The resulting Pp_k calculations quickly reduced to below 1.0. This drop was accounted for by both O1212 and T121223 and the probe frequency increased so that each part in the array was probed.

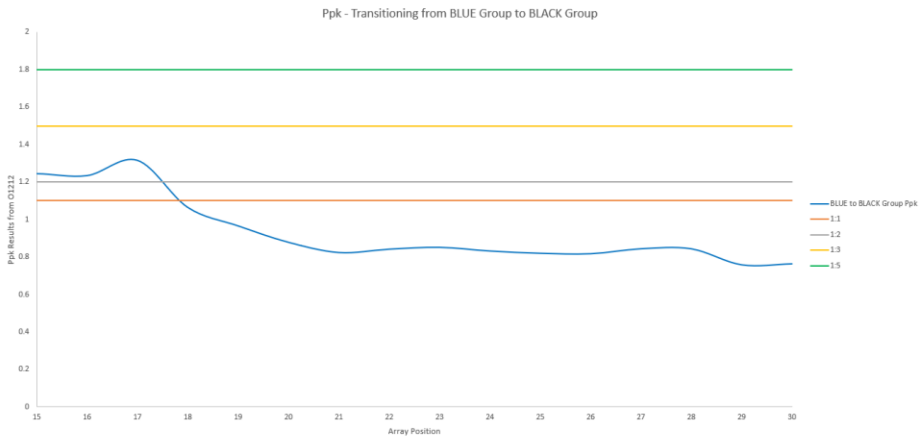

Figure 21 - Transitioning from BLUE Group to BLACK

7.4. Conclusion

The adoption of closed-loop CNC manufacturing, facilitated by on-machine probing represents a significant advancement in the quest for manufacturing optimisation. By harnessing the power of real-time data feedback and adaptive control, manufacturers can achieve heightened operational efficiency, superior product quality, and sustained operational excellence. As the industry continues to embrace these advanced manufacturing technologies, the integration of closed-loop systems in CNC manufacturing is poised to play a pivotal role in shaping the future of production optimisation.

Making use of Macro B programming methods and the logic it allows a user to add to a program, together with the intelligent use of variables it has been shown possible to create a closed-loop system in a CNC machine which react to variations in PCI data. The research undertaken in this section has proven that the logic necessary for such decision making and functionality to affect a closed-loop system is possible using only G-code and Macro B programming methods and that both main and sub programs are able to function cooperatively to update variables that results in the optimisation of throughput in a CNC machining centre resulting in optimised throughput by varying probing frequencies.

Utilising the work of Ali, et al. (2008), and using sample sizes of 15 not only free's up variables but also allows the closed loop to come into effect sooner and display process variability more accurately than with a larger sample size (Ali, et al., 2008).

Placing the necessary calculations and logic in a sub program allows for easier part programming as all of the necessary logic would not need to be added, thus not adding complexity and time to the creation of NC programs. Making use of sub programs also reduces the chances of the critical logic being altered by unassuming operators as they will not be able to easily alter any logic or calculations required for this particular closed-loop system to function

8. Research Conclusion

8.1. Conclusion

The research presented focuses on the development and implementation of closed-loop CNC systems, specifically the integration of probing cycles in CNC machining processes to establish a closed-loop system. The text outlines the methodology, expected outcomes, and results of the research, demonstrating the potential for significant cycle time reduction and improved adaptability to variations in material properties and part characteristics. The integration of on-machine probing and tool measurement systems is shown to contribute to the optimisation of the manufacturing process. The research also emphasises the need for dynamic adaptation of probing strategies to align with evolving process capability and part variation dynamics.

Eldessouky, et al. (2015) emphasise that closed-loop CNC manufacturing holds great potential for optimising manufacturing processes by continuously monitoring and adjusting the machining process to minimise errors, reduce scrap rates, and optimise production efficiency. The integration of probing cycles in CNC machining processes enables the establishment of a closed-loop system, leading to improved efficiency and reduced scrap rates (Kumar, et al., 2007). Additionally, the research highlights the importance of dynamically adapting probing strategies to align with evolving process capability and part variation dynamics (Eldessouky, et al., 2015).

The expected outcomes of the research include the dynamic adjustment of probing frequencies based on gathered data, leading to reduced probe usage and cycle times for higher Pp_k values. Additionally, the closed-loop system is expected to demonstrate improved adaptability to variations in material properties and part characteristics, resulting in reduced scrap rates and optimised manufacturing processes (Eldessouky, et al., 2015). The results presented in the text indicate variations in cycle times for different test groups, with the WHITE group showing the largest cycle time reduction due to the integration of probing cycles and the calculated Pp_k values.

This research has also set out the steps to be taken in determining the suitability of a given CNC machining centre. Sections 1 through 3 of this research can be followed to ascertain the suitability of equipment identified for use in a closed-loop manufacturing system.

In conclusion, the research presented demonstrates the potential for significant improvements in manufacturing processes through the development and implementation of closed-loop CNC systems. The integration of probing cycles and on-machine measurement technologies shows promise in reducing scrap rates, optimising production efficiency, and maintaining superior product quality. The dynamic adaptation of probing strategies to align with evolving process capability and part variation dynamics is essential for realising the full potential of closed-loop CNC systems in industrial applications. This aligns with established principles and practices in the field of closed-loop CNC machining and inspection, emphasising the integration of measuring technology, preservation of results, and the development of sophisticated control strategies to maintain an optimal balance between probing operations and overall manufacturing efficiency (Eldessouky, et al., 2015).

The research presented is aligned with established principles and practices in the field of closed-loop CNC machining and inspection, emphasising the integration of measuring technology, preservation of results, and the development of sophisticated control strategies to maintain an optimal balance between probing operations and overall manufacturing efficiency (Eldessouky, et al., 2015).

8.2. Further Research

8.2.1. Different Metrics for Determining Probing Frequencies

8.2.1.1. More Suitable PCIs

This research chose Pp_k as the appropriate PCI to determine probing frequencies due to its ability to handle unstable processes and deal with subgroup variability (Steiner, et al., 2000). However, as mentioned earlier there are far more PCIs available though they may not be as commonly known or used. It would be prudent to investigate the effects of using these lesser-known PCIs in such a closed-loop system that this research has described. While the logic needed to ensure that throughput is optimised would be the same, the methods of calculating the PCI data will alter. This should not cause any issues providing the NCU can accurately calculate the data. The use of a reduced sample size 15 to more accurately show the variation of the process (Ali, et al., 2008) allowed the closed loop to function more quickly but it is hoped that future research will determine a more accurate PCI.

8.2.1.2. Deviation from Nominal and SPC/EPC

In manufacturing, SPC is used to monitor processes and identify any deviations from the nominal or target values (Heigl, et al., 2021). This is achieved through the use of control charts, such as the individual observations (I-chart), which help in detecting any assignable causes of variation. SPC is essential for ensuring that the process remains in a stable state and meets the desired quality standards. Deviations from the nominal values can indicate potential issues in the manufacturing process, and SPC helps in identifying and addressing these deviations to maintain product quality and process efficiency (Zhang, et al., 2008).

The combination of SPC with Engineering Process Control (EPC) has been shown to be effective in reducing production disruptions in manufacturing industries (Smew, et al., 2020). EPC is concerned with adjusting system inputs to keep the system output on target, while SPC is used to monitor processes and identify any assignable causes of variation. By integrating these two approaches, manufacturing processes can be better controlled, and disruptions minimised.

Overall, monitoring deviations from the nominal values in manufacturing SPC is crucial for ensuring product quality, identifying process issues, and maintaining process efficiency. By using control charts and integrating SPC with EPC, manufacturing industries can effectively monitor and control their processes to minimise disruptions and improve product quality (Smew, et al., 2020).

Early in this research the decision was made to not make use of the deviation from nominal and SPC methods over concerns that the amount of data to be processed would result in a complex program and the increased variable usage. Another factor contributing to its disqualification is that SPC tends to be a visual representation of process performance that would not be displayable on older CNC machines and could lead to operators not understanding the information collected and calculated.

However, using this method would still result in the same functioning closed-loop system. This research believes that this method of determining probing frequencies should be investigated to determine suitability for manufacturing.

8.2.2. Calibration Programs

Section 3 of this research highlighted that the Type 1 R&R and Bland-Altman tests are reliant on accurate fixturing and test parts. To overcome this issue, a purpose-built calibration artifact should be built using a material that is more resistant to temperature fluctuations. A calibration program consisting of a Type 1 and Bland-Altman test, as well as testing the NCUs ability to handle calculations should also be created in parallel. Integrating the probe stylus calibration can also help if dealing with older equipment as errors from the probe length and triggering forces required can be accounted for without the need for extra investigative work (Wozniak, et al., 2013).

The use of such an artifact and calibration program would automate the majority of the work carried out in sections 2 and 3 and could further increase the rate of adopting closed-loop methodologies in manufacturing and provide users with a consistent baseline when comparing new and older equipment.

8.2.3. Export of Variables to MRP Systems

Macro B allows the import and export of data through a CNC machines RS-232 communication ports (Lynch, 1997). This would allow the export of key variables from the NCU for use in either an SPC system or fed into an MRP database. This can be a relatively low-cost solution of exporting data as setting up the NCU and the receive computer need only have the necessary ports configured (Smid, 2005).

This built in functionality and low-cost data transfer method would allow users to consider the performance of each machine running a closed loop system described in this research and begin to take advantage of closed loop supply chain management. Manufacturers would be able prioritise certain equipment based on the urgency of the orders. Supply chain management is gaining more attention not just in industry but also academia (Sherafati & Bashiri, 2016), and will likely grow further as the concept of the circular economy grows. Industry 4.0 is placing premeasure on SMEs to make their processes and operation more sustainable (Kumar, et al., 2020). Making use of this built in functionality will be another way in which SMEs can progress further in the world of I4.0 and increased efficiencies with little financial investment.

8.2.4. Integration with STEP-NC

STEP-NC is a standard that provides a rich information model for CNC machining centres. It is designed to replace traditional G-code programming used in CNC machining to allow a higher level of information exchange between CAD/CAM systems and CNC machines. This novel approach enables CNC machines to make decisions on “what to do”, rather than “how to do” a specific task. Controlled under the standard ISO 14649, STEP-NC aims to improve manufacturing efficiency and is intended to facilitate on-machine inspection and provide a more adaptable CNC system (Um, et al., 2016).

STEP-NC seeks to provide a standardised format for conveying all the information necessary to manufacture a product including tool path and process data (Mileski, et al., 2022). By adopting STEP-NC, older CNC machines can potentially support a wider range of manufacturing processes and adapt to changes in production requirements more easily (Zivanovic, et al., 2023). By integrating the data generated by implementing the above research with STEP-NC, users will be able to consider the ability of a CNC to hold given tolerances and be able to program accordingly thanks to the bi-directional data exchange STEP-NC provides (Brecher, et al., 2006).

There are a number of considerations and challenges with integrating STEP-NC, particularly with older machinery. It is essential to assess whether older CNC machines have the necessary capabilities to leverage the features offered by STEP-NC. Older CNC machines may not fully support the STEP-NC standard, requiring hardware and software upgrades or retrofits (Zivanovic, et al., 2023). This can add cost and the initial investment in upgrading older CNC machines to support STEP-NC will need to be justified by the expected improvements to productivity and the addition of extra capabilities of a CNC machine (Muhammad & Nu'man, 2022). There is also a requirement for knowledge and expertise of ISO 146949 and implementing STEP-NC. This could necessitate training for the existing workforce or possibly hiring new employees that already have the required skillset (Zivanovic, et al., 2023).

In conclusion, integrating STEP-NC with older CNC machining centres offers the potential for improved interoperability, flexibility, and information management in the manufacturing process. However, this process also presents challenges related to compatibility, training, and cost. Careful consideration of the benefits, challenges, and specific circumstances of each manufacturing environment is essential to make an informed decision about integrating STEP-NC with older CNC machining centres.

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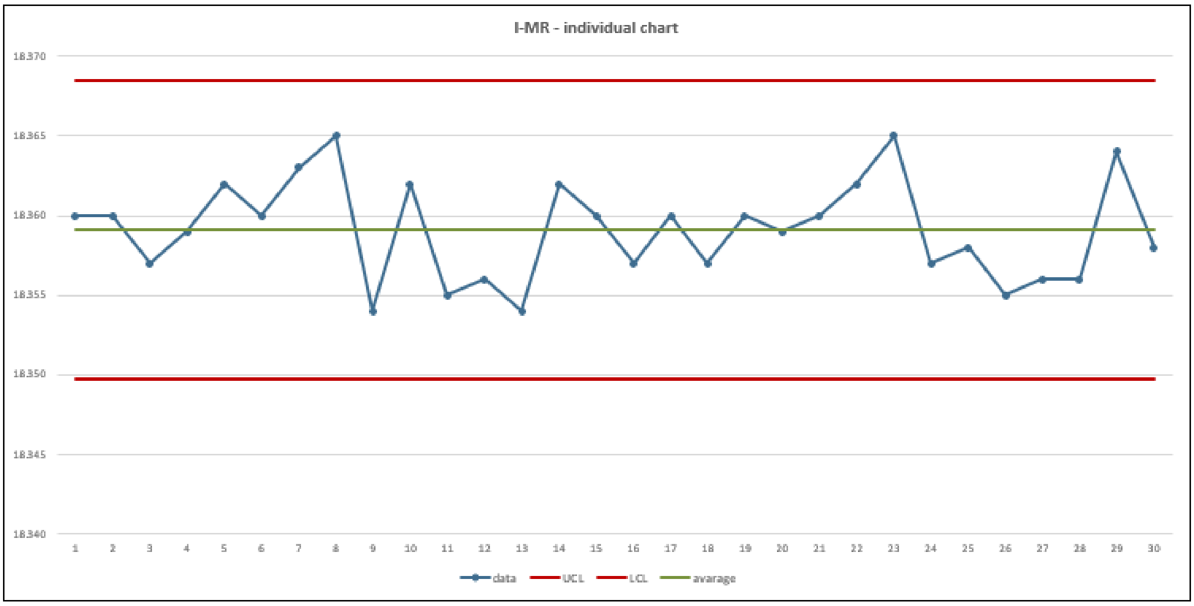
10.Appendix

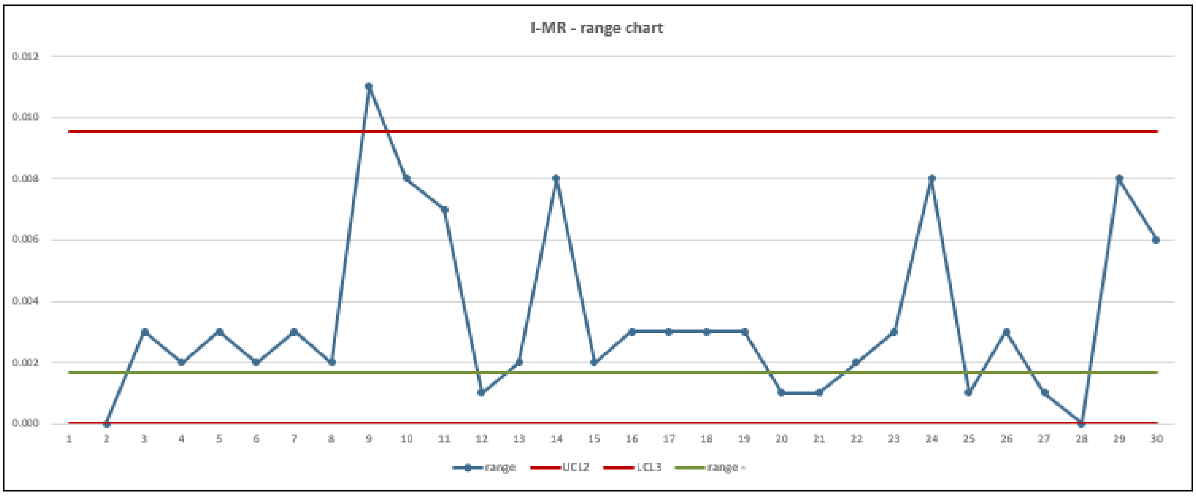
10.1. Section 2 Test data

Range:13.80 – 14.20 Ppk<1.0			Range:13.90 – 14.10 Ppk<1.5			Range:13.95 – 14.05 Ppk>1.5		
A	B	C	D	E	F	G	H	I
13.958280	14.078219	14.072155	14.036213	13.967716	13.936998	13.966085	13.984699	13.979292
13.818620	14.023479	14.012786	14.062487	13.990010	14.022648	14.020947	14.009496	14.044874
13.976278	14.137841	14.033246	13.935514	13.948012	14.004242	13.991335	14.031582	14.047027
14.092575	14.146295	13.819155	13.935633	14.035014	13.925901	13.956829	13.953525	13.972573
13.808322	14.065515	13.929415	14.008524	14.079875	14.064887	13.983432	14.011118	14.031935
13.860011	13.993400	14.083951	13.975670	14.033781	14.093693	14.005200	13.976535	14.031518
13.832242	14.082737	13.830646	14.051087	14.046451	13.955786	13.973530	13.977950	13.968364
14.164435	14.051953	13.932628	14.065931	13.935482	13.965604	13.958164	14.013446	13.987720
14.047047	14.008829	14.045847	14.024740	14.040439	14.092342	14.033346	14.019010	14.027307
14.042209	13.832493	13.962404	14.022871	14.011382	13.910316	13.957245	14.004221	13.980513
13.890303	14.171370	14.088277	13.934452	13.990225	13.948534	14.046216	13.961225	13.997683
14.020315	13.996121	13.948335	13.998215	13.952360	13.976424	14.021070	14.014937	14.008521
13.839202	13.977208	13.955346	14.010737	14.008037	14.003153	13.979291	14.045900	13.964180
13.939602	14.056628	14.028974	13.937852	14.069841	13.971799	13.967149	14.004781	13.990936
13.977747	14.163557	14.016861	13.922512	14.093169	14.005906	14.011867	14.032360	13.970881
14.193832	13.894619	13.852783	14.083640	13.901856	14.040107	13.990503	13.979535	14.029108
14.108909	14.126457	13.971595	14.010902	13.961788	13.986366	13.997874	14.035907	13.985033
13.987705	13.956817	14.186692	13.906155	13.940184	13.943768	13.963152	13.966867	14.044705
14.102275	13.840578	13.811481	13.922092	13.950363	14.030333	13.951891	13.985074	14.009977
14.049627	14.006526	14.134193	14.011441	13.946681	13.940513	13.997807	14.019974	14.030146
14.014064	14.003317	13.800067	14.076280	14.075054	13.949620	14.034818	14.030279	13.988423
13.964078	13.871441	13.980744	14.075158	13.959012	14.098230	14.042792	13.988481	14.034178
14.073457	14.060545	14.167818	13.941126	13.931515	13.915107	13.978844	14.032126	14.010669
13.983542	13.969338	14.010326	14.083880	13.935231	13.926184	14.038240	14.036126	13.954397
13.928505	13.816217	14.147455	13.938700	13.933807	14.091688	14.002991	14.006101	14.009533
13.931302	13.879519	14.133851	14.019802	14.066820	13.962844	13.976137	13.955717	14.028387
13.829113	14.030514	13.859565	13.907080	14.060761	14.014801	13.985875	13.994522	14.048804
13.993647	13.988332	13.863344	14.050687	13.919794	13.943913	14.028016	13.956438	13.990729
14.081298	14.084583	13.956675	13.995712	13.939680	14.083634	14.008508	14.020120	13.982920
13.826153	14.117496	14.110094	13.949726	13.930468	14.071776	13.957975	14.036550	14.011146

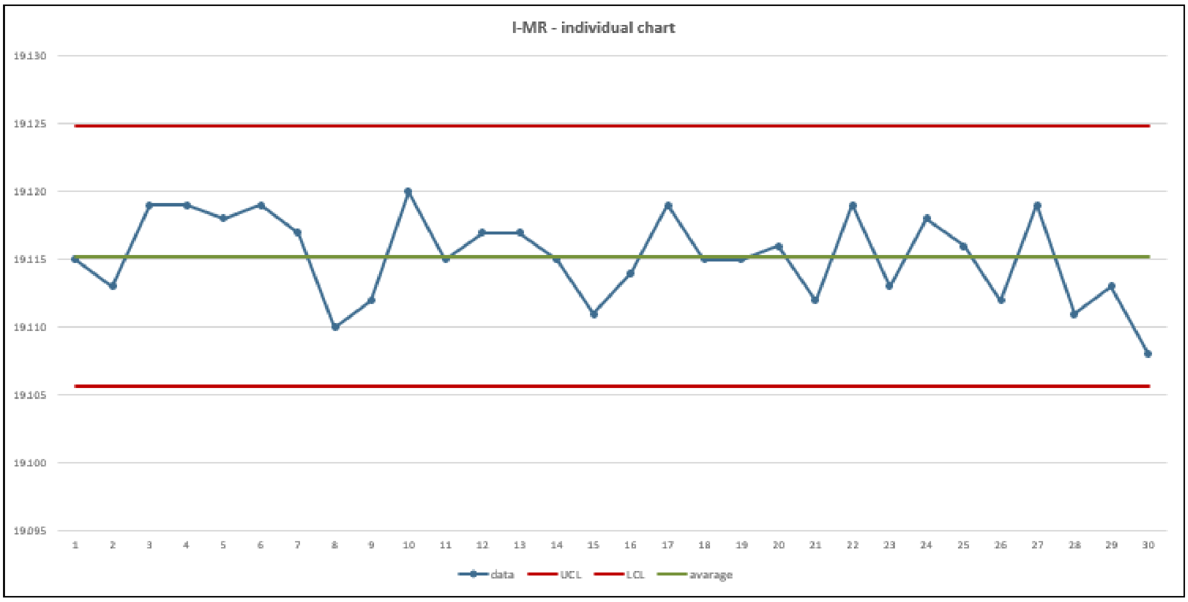
10.2. Section 3 - Type 1 R&R Charts

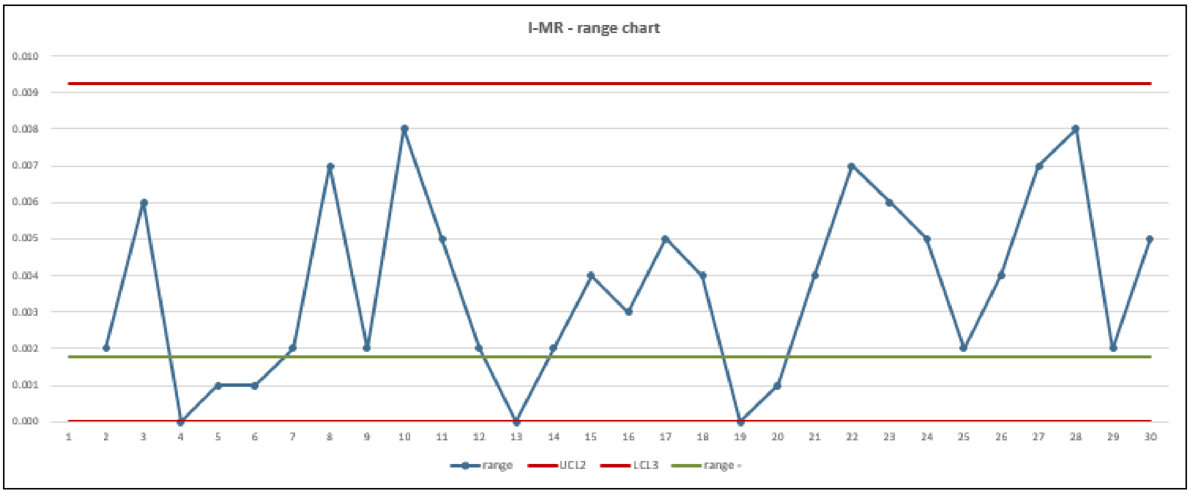
10.2.1. BLACK Group



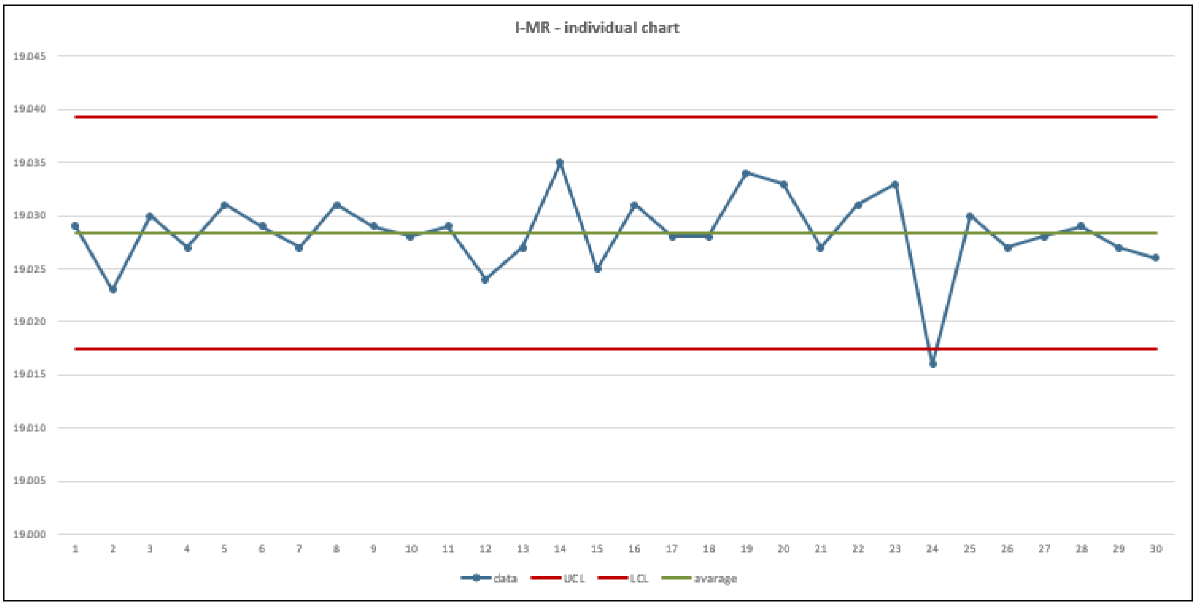


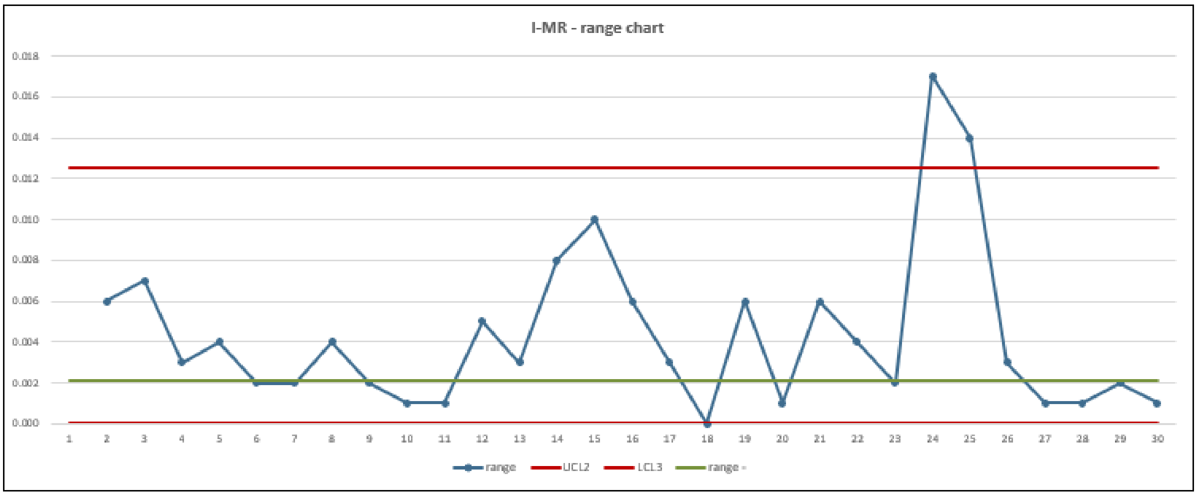
10.2.2. BLUE Group





10.2.3. WHITE Group





10.3. Section 3 – Bland-Altman Results

10.3.1. BLACK Group

Part	CMM Measurement	CNC Measurement 1	CNC Measurement 2	CNC Measurement 3
1	19.56	19.574	19.579	19.576
2	19.551	19.551	19.552	19.559
3	19.538	19.539	19.539	19.536
4	19.473	19.48	19.477	19.477
5	19.371	19.39	19.381	19.382
6	19.37	19.408	19.402	19.408
7	19.291	19.294	19.274	19.295
8	19.183	19.188	19.19	19.19
9	19.171	19.18	19.176	19.175
10	19.124	19.13	19.124	19.135
11	19.089	19.101	19.097	19.095
12	19.083	19.098	19.095	19.096
13	19.069	19.074	19.063	19.066
14	19.063	19.067	19.065	19.069
15	18.996	18.997	19.002	18.999
16	18.974	18.965	18.963	18.969
17	18.933	18.939	18.943	18.948
18	18.916	18.933	18.931	18.939
19	18.883	18.891	18.889	18.886
20	18.867	18.876	18.873	18.871
21	18.826	18.843	18.839	18.837
22	18.826	18.836	18.83	18.831
23	18.675	18.681	18.683	18.679
24	18.555	18.567	18.57	18.558
25	18.54	18.54	18.54	18.543
26	18.515	18.517	18.517	18.515
27	18.478	18.48	18.482	18.481
28	18.453	18.463	18.458	18.465
29	18.364	18.362	18.366	18.364
30	18.354	18.36	18.358	18.357

10.3.2. BLUE Group

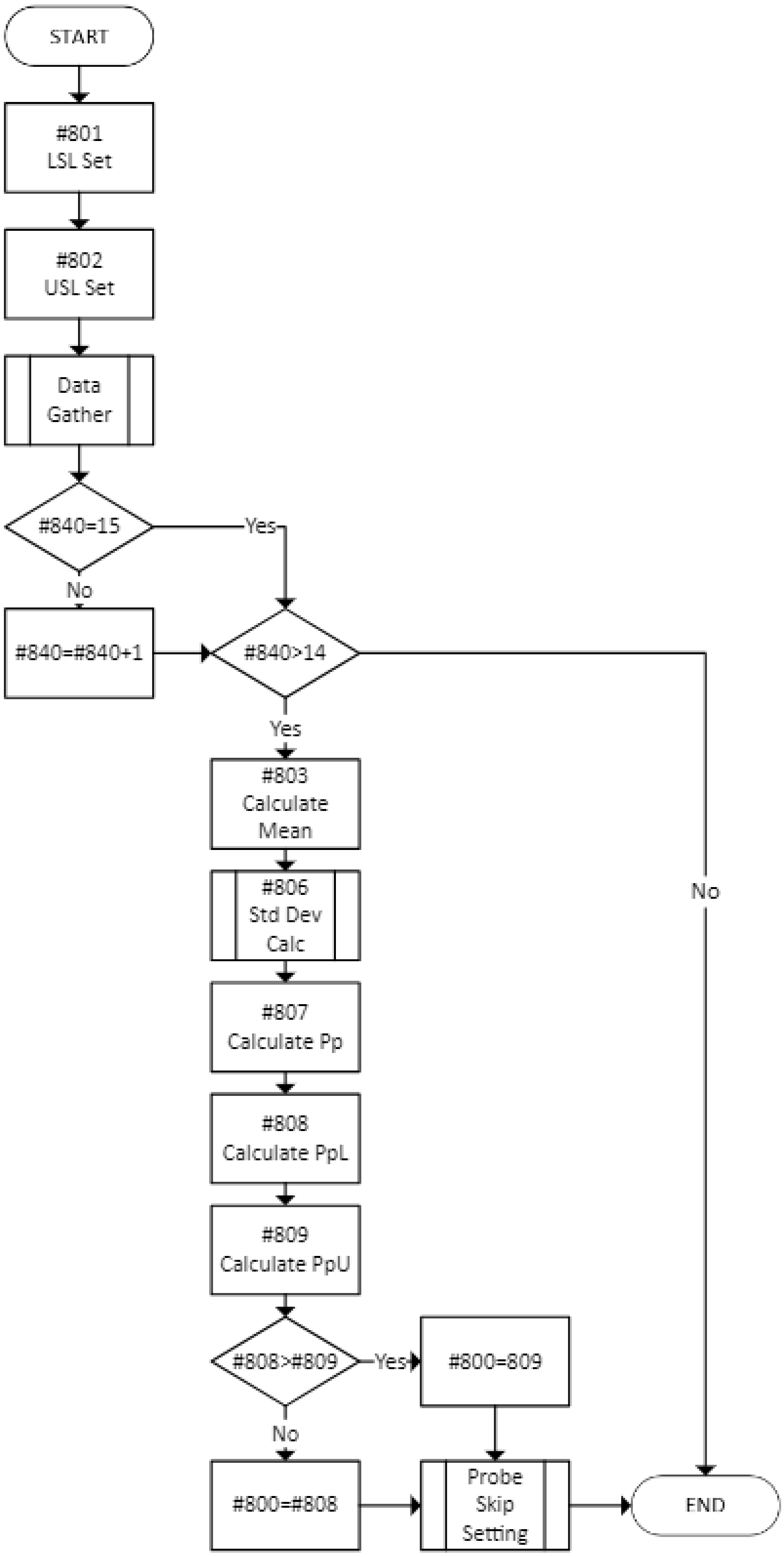
Part	CMM Measurement	CNC Measurement 1	CNC Measurement 2	CNC Measurement 3
1	18.656	18.638	18.63	18.624
2	18.887	18.896	18.899	18.882
3	18.533	18.545	18.55	18.533
4	18.734	18.74	18.739	18.728
5	19.116	19.121	19.12	19.105
6	18.839	18.847	18.848	18.828
7	18.839	18.849	18.841	18.842
8	18.656	18.672	18.67	18.652
9	19.227	19.234	19.224	19.209
10	18.871	18.873	18.87	18.858
11	19.381	19.393	19.393	19.381
12	19.116	19.116	19.121	19.103
13	19.507	19.495	19.502	19.502
14	19.445	19.449	19.45	19.452
15	19.307	19.313	19.31	19.303
16	19.342	19.351	19.352	19.329
17	19.028	19.037	19.041	19.022
18	19.252	19.268	19.262	19.255
19	18.94	18.944	18.948	18.938
20	18.828	18.814	18.811	18.804
21	19.227	19.232	19.223	19.216
22	18.918	18.923	18.916	18.91
23	18.887	18.889	18.887	18.873
24	19.224	19.225	19.226	19.207
25	18.878	18.876	18.872	18.865
26	18.828	18.828	18.831	18.822
27	19.116	19.122	19.123	19.109
28	18.913	18.912	18.922	18.897
29	18.918	18.92	18.912	18.907
30	18.985	18.99	18.989	18.984

10.3.3. WHITE Group

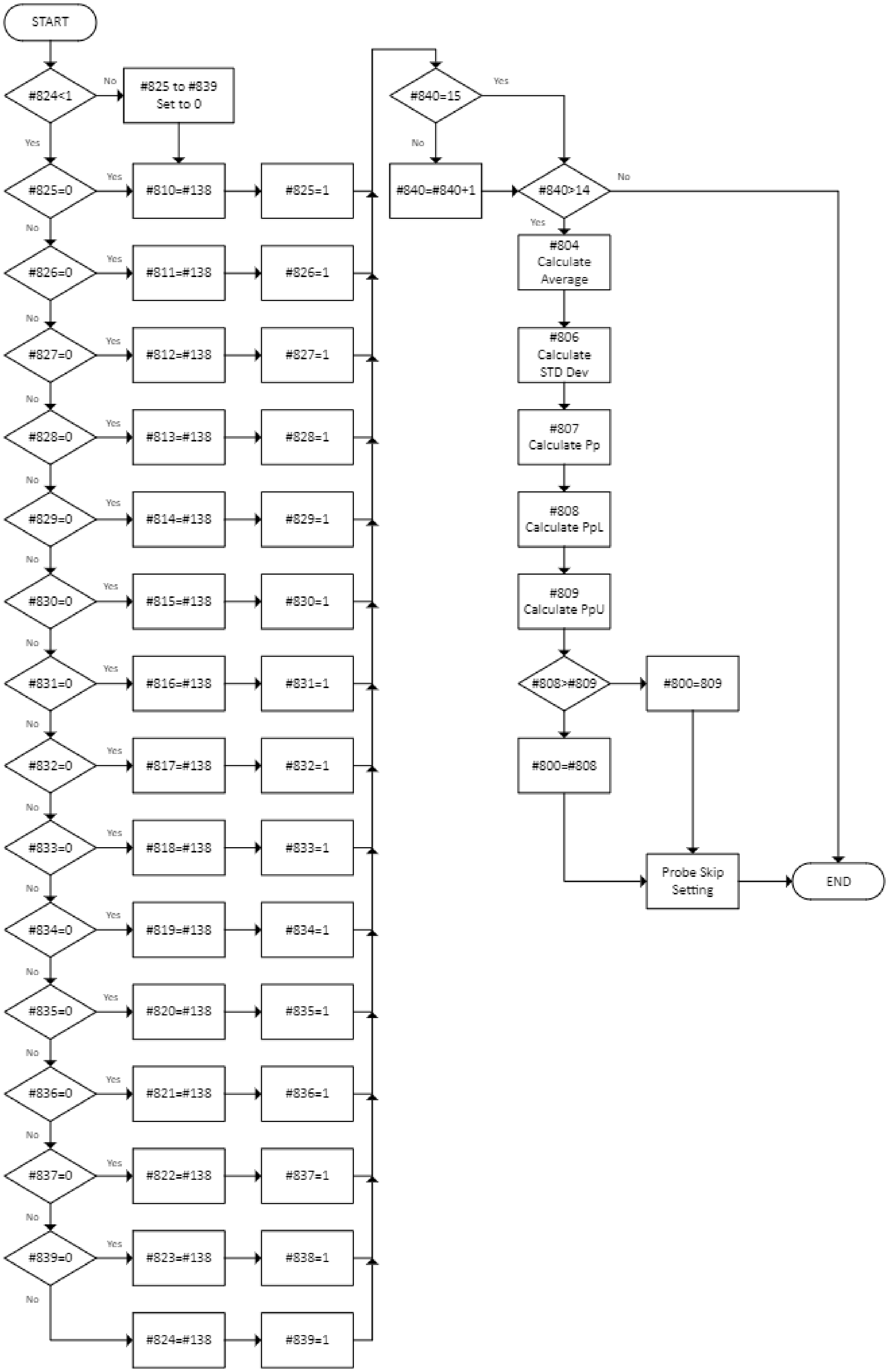
Part	CMM Measurement	CNC Measurement 1	CNC Measurement 2	CNC Measurement 3
1	19.266	19.272	19.273	19.278
2	19.265	19.264	19.269	19.267
3	19.256	19.256	19.259	19.251
4	19.232	19.236	19.232	19.233
5	19.241	19.234	19.229	19.234
6	19.186	19.198	19.188	19.189
7	19.183	19.183	19.180	19.174
8	19.122	19.119	19.115	19.119
9	19.104	19.106	19.100	19.098
10	19.100	19.102	19.101	19.099
11	19.080	19.081	19.083	19.072
12	19.058	19.069	19.069	19.058
13	19.029	19.032	19.026	19.019
14	19.025	19.022	19.019	19.012
15	19.024	19.019	19.014	19.014
16	19.000	19.000	18.990	18.992
17	18.962	18.957	18.962	18.963
18	18.919	18.918	18.923	18.919
19	18.896	18.884	18.886	18.889
20	18.869	18.846	18.849	18.854
21	18.838	18.836	18.833	18.836
22	18.794	18.792	18.786	18.790
23	18.794	18.789	18.799	18.797
24	18.775	18.769	18.780	18.777
25	18.775	18.771	18.768	18.773
26	18.758	18.757	18.754	18.753
27	18.758	18.746	18.746	18.754
28	18.741	18.738	18.733	18.733
29	18.727	18.721	18.722	18.716
30	18.713	18.715	18.708	18.710

10.4. O1212 Logic and Flow Diagrams

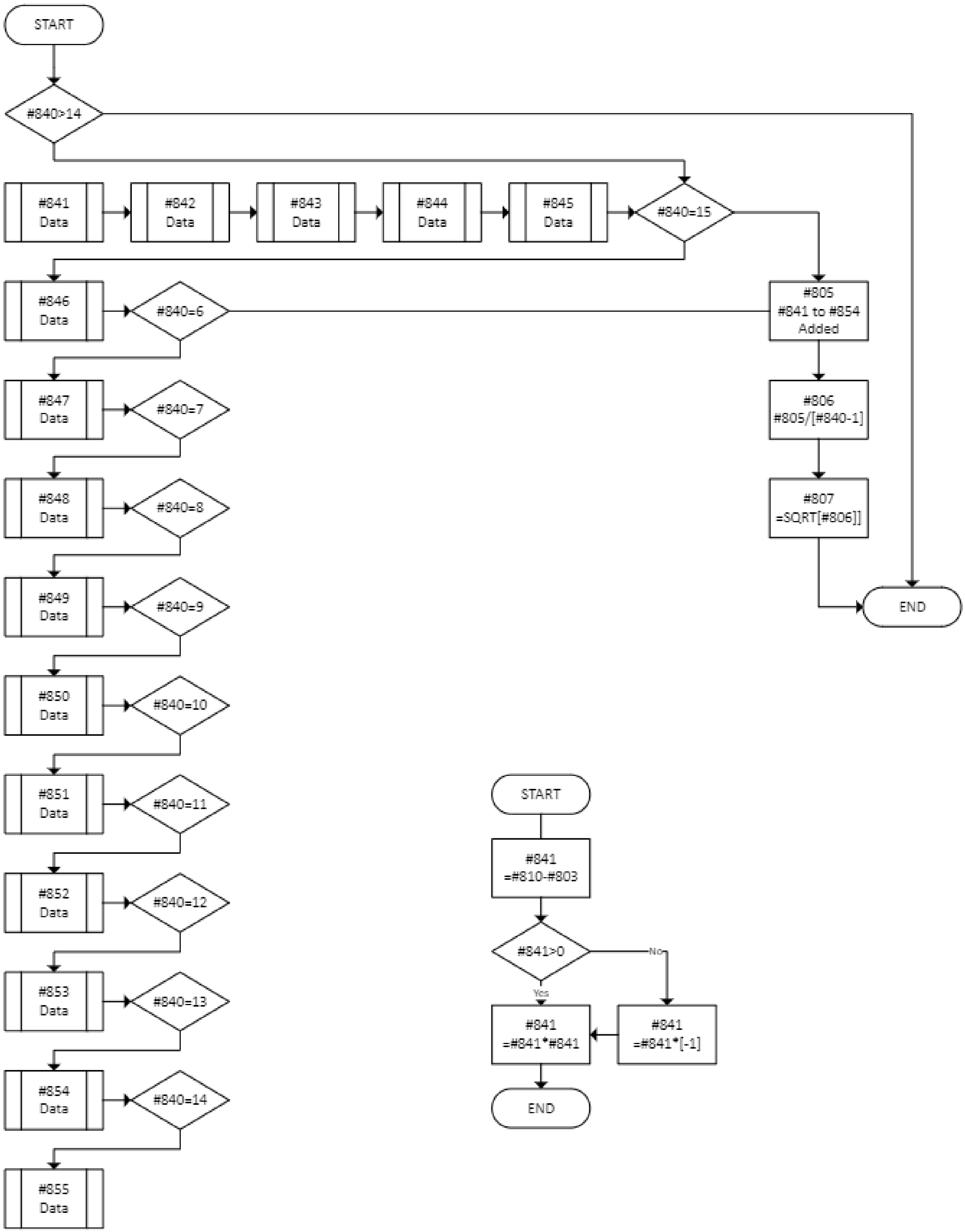
10.4.1. O1212 – Overview Process Flow Diagram



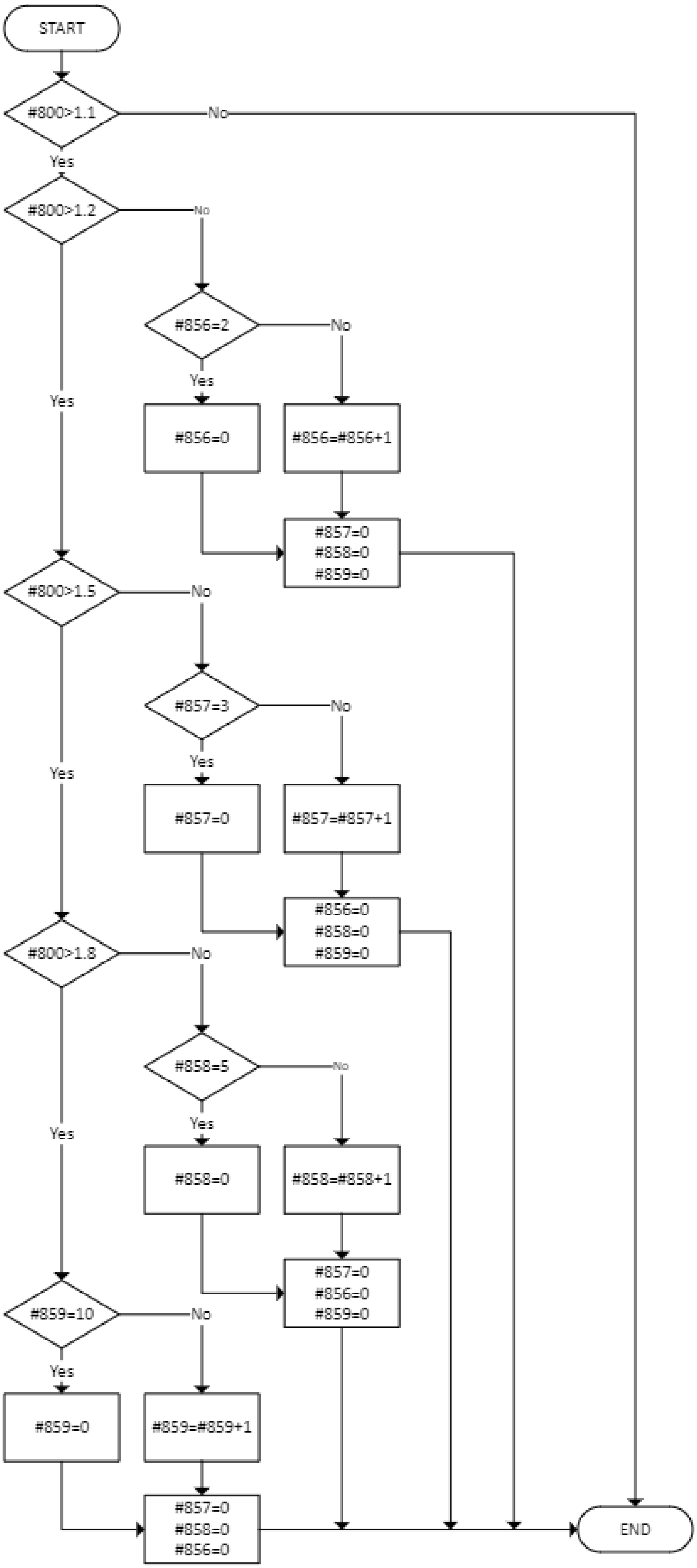
10.4.2. O1212 – Data Probed Data Gathering Process Flow Diagram



10.4.3. O1212 – Standard Deviation Data Formatting & Calculation Flow Diagram



10.4.4. O1212 – Probing Frequency Control Process Flow Diagram



10.4.5. O1212 – Macro Variable Assignments

#800 - Ppk
#801 - LSL
#802 - USL
#803 - Mean Calc 1
#804 - Std Dev Calc 1
#805 - Std Dev Calc 2
#806 - Std Dev Calc 3
#807 - Pp
#808 - PpL
#809 - PpU
#810 - Data Point 1
#811 - Data Point 2
#812 - Data Point 3
#813 - Data Point 4
#814 - Data Point 5
#815 - Data Point 6
#816 - Data Point 7
#817 - Data Point 8
#818 - Data Point 9
#819 - Data Point 10
#820 - Data Point 11
#821 - Data Point 12
#822 - Data Point 13
#823 - Data Point 14
#824 - Data Point 15
#825 - Data write 1
#826 - Data Write 2
#827 - Data Write 3
#828 - Data write 4
#829 - Data write 5
#830 - Data write 6
#831 - Data write 7
#832 - Data write 8
#833 - Data write 9
#834 - Data write 10
#835 - Data write 11
#836 - Data write 12
#837 - Data write 13
#838 - Data write 14
#839 - Data write 15
#840 - Data Point Counter
#841 - Std Dev Data 1
#842 - Std Dev Data 2
#843 - Std Dev Data 3
#844 - Std Dev Data 4
#845 - Std Dev Data 5
#846 - Std Dev Data 6
#847 - Std Dev Data 7
#848 - Std Dev Data 8
#849 - Std Dev Data 9
#850 - Std Dev Data 10
#851 - Std Dev Data 11
#852 - Std Dev Data 12
#853 - Std Dev Data 13
#854 - Std Dev Data 14
#855 - Std Dev Data 15
#856 - Probe Skip 1
#857 - Probe Skip 2
#858 - Probe Skip 3
#859 - Probe Skip 4

10.4.5.1. Flow Diagram of Throughput Optimisation in a Machining Operation