DEVELOPMENT OF ISO 23704 STANDARDISED CYBER-PHYSICAL PRODUCTION ENVIRONMENT FOR ON-LINE DIMENSIONAL QUALITY CONTROL

M.Tech. Thesis

By

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DEVELOPMENT OF ISO 23704 STANDARDISED CYBER-PHYSICAL PRODUCTION ENVIRONMENT FOR ON-LINE DIMENSIONAL QUALITY CONTROL

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **" DEVELOPMENT OF ISO 23704 STANDERDISED CYBER-PHYSICAL PRODUCTION ENVIRONMENT FOR ON-LINE DIMENSIONAL QUALITY CONTROL "** in the partial fulfilment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DISCIPLINE OF MECHANICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from August 2022 to June 2024 under the supervision of **Dr. Vibhor Pandhare, Assistant Professor, IIT Indore**. .

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

07/06/24

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This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

June 7, 2024

Signature of the Supervisor of

M.Tech Thesis

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Signature of Supervisor of M.Tech. thesis

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ABSTRACT

Industry 4.0 can be described as a transition towards a significant increase in making data-driven decisions across the global value-chain. Big Data, Industrial Internet of Things, Cyber-Physical Systems, Additive Manufacturing, Artificial Intelligence, etc. are some of the key enablers for Industry 4.0. The convergence of cyber-physical systems and product lifecycle management presents an unprecedented opportunity to revolutionize manufacturing practices within the framework of Industry 4.0. At the forefront of this technological wave is Additive Manufacturing (AM), rapidly establishing itself as a mainstream method in the manufacturing landscape. This attraction is fuelled by the potential to create novel designs, intricate features, lightweight structures, and the advantageous low material usage provided by AM. However, to fully harness the potential of AM, it is imperative to evolve monitoring methodologies commensurate with this paradigm shift.

A machine is considered "smart" when it can perform the given tasks autonomously while make informed decisions and adapting to changing circumstances without constant human intervention. This work highlights the critical importance of combining Cyber-Physical Systems with Additive Manufacturing to optimize the process and improve product integrity. The proposed system employs a network of sophisticated sensors, particularly optical rotary encoders, and a comprehensive data collection system to continuously monitor key process parameters such as nozzle position, speed, and acceleration for a Fused-Deposition Modelling (FDM) process. By implementing real-time data analytics, the system can promptly detect and correct anomalies, which helps maintaining stringent quality control throughout the manufacturing process.

The primary objectives include in-situ monitoring of the FDM printing process for geometric variations due to mechanical movements, developing a data acquisition system to integrate design and production data, and using open-source technologies for replicable implementation. Additionally, the work aims to standardize the developed system with ISO 23704.

A data collection system using optical rotary encoders was developed to monitor the FDM process, ensuring comprehensive documentation and detailed analysis of the workflow. An analysis algorithm based on comparing the tool movement with the design enables real-time error calculation during the FDM process, allowing immediate detection and correction of

discrepancies, significantly improving product accuracy. The monitoring system, standardized according to ISO 23704, meets quality requirements, enhancing credibility and reliability. The system's replicability was tested across multiple FDM machines, demonstrating its reliability and versatility in different environments. It was also used for reverse engineering products developed through FDM, providing valuable insights for post-process analysis and product improvements.

The novelty lies in its detailed error analysis methodology, utilizing baseline error patterns as reference standards by comparing real-time manufacturing data with CAD designs. This facilitates early detection as well as quantification of the degree of deviations, minimizing defects and reducing material waste. The system's reliability and effectiveness were validated on two different FDM machines with faults induced at various levels, ensuring robustness and replicability of the results.

In conclusion, this study presents a new standardized approach for online monitoring of AM processes, ensuring high product quality and enhancing manufacturing efficiency. This research supports the broader goals of Industry 4.0, leading to smarter, more responsive, and efficient manufacturing practices.

Future work will involve analysing more complex designs to assess the system's performance with intricate structures, evaluating various design parameters, identifying potential issues, and ensuring the system can handle these complexities without compromising performance or quality. Streamlining the data collection process to better integrate with FDM machine control will require optimizing data acquisition methods, ensuring real-time data transfer, and minimizing data loss. Developing a behaviour model Additive manufacturing workflow that complies with ISO 23704 standards will be crucial future development. Future efforts will also focus on creating a prediction model for surface roughness (Ra) to improve quality control, involving data collection and analysis of surface roughness and developing a model that can accurately predict Ra based on key influencing factors.

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ABBREVIATIONS

CPS	Cyber-Physical System
CPPS	Cyber-Physical Production System
PLM	Product Lifecycle Management
CPSMT	Cyber Physically Smart Machine Tool
CPCM	Cyber-Physically Controlled Machine tool
CSSM	Cyber Support System for Machine Tool
SFDS	Shop Floor Device System
SFCS	Shop Floor Control System
UIS	Unified Interface System
SAMS	Smart Additive Manufacturing System
DT	Digital Twin
AI	Artificial Intelligence
ML	Machine Learning
AM	Additive Manufacturing
IOT	Internet of Things
CAD	Computer Aided Design
POC	Proof-of-Concept
DCS	Data Collection System

Chapter 1 Introduction

Industry 4.0 and smart manufacturing are revolutionizing the process utilized for production, steering in an era of efficiency and innovation. At the core of this transformation lie several key technological pillars like big data, Artificial Intelligence (AI), Machine Learning (ML), Additive Manufacturing, Cyber-Physical Systems **[1]** etc. Together, these components provide a manufacturing environment where machines are self-aware and have the ability to make decisions on their own, rather than only being just a tool.

One of the central concepts of Industry 4.0 is the integration of advanced digital technologies into the manufacturing process. Big data plays a crucial role in this integration by providing manufacturers with access to vast amounts of information about their operations. By analysing this data, manufacturers can gain valuable insights into their processes, identify inefficiencies, and make data-driven decisions to optimize production. This ability to harness data for improved decision-making is fundamental to the concept of smart manufacturing.

Artificial intelligence and machine learning are also critical enablers of Industry 4.0. These technologies allow machines to learn from experience, adapt to changing conditions, and make predictions based on patterns in data. In manufacturing, AI and ML algorithms can be used to optimise production schedules, predict equipment failures before they occur, and even automate quality control processes. By leveraging AI and ML, manufacturers can achieve higher efficiency, productivity, and quality in their operations.

Cyber-physical systems (CPS) represent the convergence of the physical and digital worlds in manufacturing. It is a set of automatic systems for collecting, processing, and analysing data **[2]**. It has widespread applications such as robotics autonomous vehicles, process control systems, etc. CPS facilitates greater automation, efficiency, and responsiveness by enabling seamless communication between machines, equipment, and other devices. Integrating physical and digital elements is essential for creating intelligent manufacturing environments. Such systems can be termed Cyber-physical Production Systems (CPPS) **[3].** It comprises a network of connected components with the field devices, machines, and production modules. In this way traditional production can be replaced with decentralised self-organization. The implementation of CPS within the shop floor environment is crucial to the realisation of Industry 4.0. Manufacturers can create interconnected systems capable of real-time data exchange and autonomous decision-making by integrating sensors, actuators, and communication networks. This integration allows for greater visibility and control over production processes, enabling companies to optimise resource allocation, minimise downtime, and improve overall productivity. One of the key drivers behind the adoption of CPS in manufacturing is the advancement of information and communication technologies. With different technologies such as the Internet of Things (IoT), cloud computing, edge computing, etc., manufacturers now have access to unprecedented data and computational power. This enables them to develop sophisticated CPSs to analyse vast amounts of data, monitor the process, predict maintenance needs, and even self-optimize production processes. The adoption of CPS within the shop floor environment signifies a fundamental shift in how manufacturing companies operate. By embracing Industry 4.0 principles, manufacturers can unlock new opportunities for innovation and competitiveness. From agile production systems to personalised products and services, the integration of interconnected intelligent components lays the foundation for a more efficient, adaptable, and resilient manufacturing ecosystem.

1.1. Cyber-Physical PLM Environment

This research proposes a novel concept: Cyber-physical Product Lifecycle Management (PLM) environment. A cyber-physical system supporting the enterprise life cycle from design and development to production, operation, and finally, end-of-life management can be imagined as a Cyber-physical PLM environment. Such systems are integrated into network throughout the entire product life cycle. By seamless linking of the virtual representation of the product with the comprehensive PLM systems, organizations can unlock a lot of advantages that drive innovation and efficiency throughout the product's lifecycle **[4].** These systems incorporate sensors, controllers, and procedure-oriented information systems into a single network that expands over the whole life of the product. We will discuss more on this in Chapter 3. One of the advantages with is Cyber-Physical PLM environment is real-time feedback loop. The Integrated data collection system will continuously gather data from sensors, IoT devices and other sources embedded with the system gathering continuous stream of information. This data is then fed back to the PLM system, providing designers, engineers, and other stakeholders with a deep understanding of how the product is being developed and is performing in the real-world conditions. With this the design iterations can be executed rapidly, decreasing the development cycle, and accelerating time-to-market. For this to establish we need what is called a "Smart Machine Tool".

1.2. Cyber-Physically controlled Smart Machine Tool Systems (CPSMT)

The backbone of cyber-physically smart machine tools lies in their comprehensive sensor networks. These sensors can continuously monitor various aspects of the machine's operation which can be temperature, vibration, force, and positional data. For example, temperature sensors help in maintaining optimal operating conditions to prevent overheating within the machine, while vibration sensors detect irregularities that could indicate wear or potential failures. Actuators, on the other hand, execute precise movements and adjustments based on sensor feedback, ensuring that the machine operates within desired parameters.

Connectivity is a key feature for a smart machine tool, enabling seamless communication within the manufacturing ecosystem. Utilizing industrial Internet of Things (IoT) protocols, these tools connect with other machines, control systems, and human operators. This connectivity facilitates synchronized operations, remote monitoring, and integration with broader enterprise resource planning (ERP) and manufacturing execution systems (MES).

The integration of advanced control systems is what truly differentiates smart machine tools from their conventional counterparts. These systems can employ sophisticated algorithms to optimize machine performance dynamically. Adaptive control, for example, allows the machine to adjust its operations in response to real-time feedback, enhancing precision and efficiency. Predictive maintenance algorithms analyze operational data to forecast maintenance needs, reducing downtime and extending the machine's lifecycle.

However, the market offers different types of smart machine tools with their own concepts and terminologies, leading to confusion among stakeholders, including end-users. This highlights the need for standards and models to clarify smart machine tool systems.

The ISO 23704 **[5]** series specifies general standards for smart machine tools that allow smart manufacturing on the shop floor using a cyber-physical system control method known as CPSMT. These requirements are crucial for ensuring compatibility with cyber-physical systems and effective integration into manufacturing environments, ultimately realizing Industry 4.0 principles.

1.3. ISO 23704

ISO 23704 provides general requirements for CPSMT's. It plays a pivotal role in guiding the development of such environments, emphasizing the need for seamless integration between digital and physical aspects of the machine. By following ISO 23704 standard, manufacturers can establish a robust foundation for managing data, processes, and resources in a unified manner, enabling better collaboration and informed decision-making.

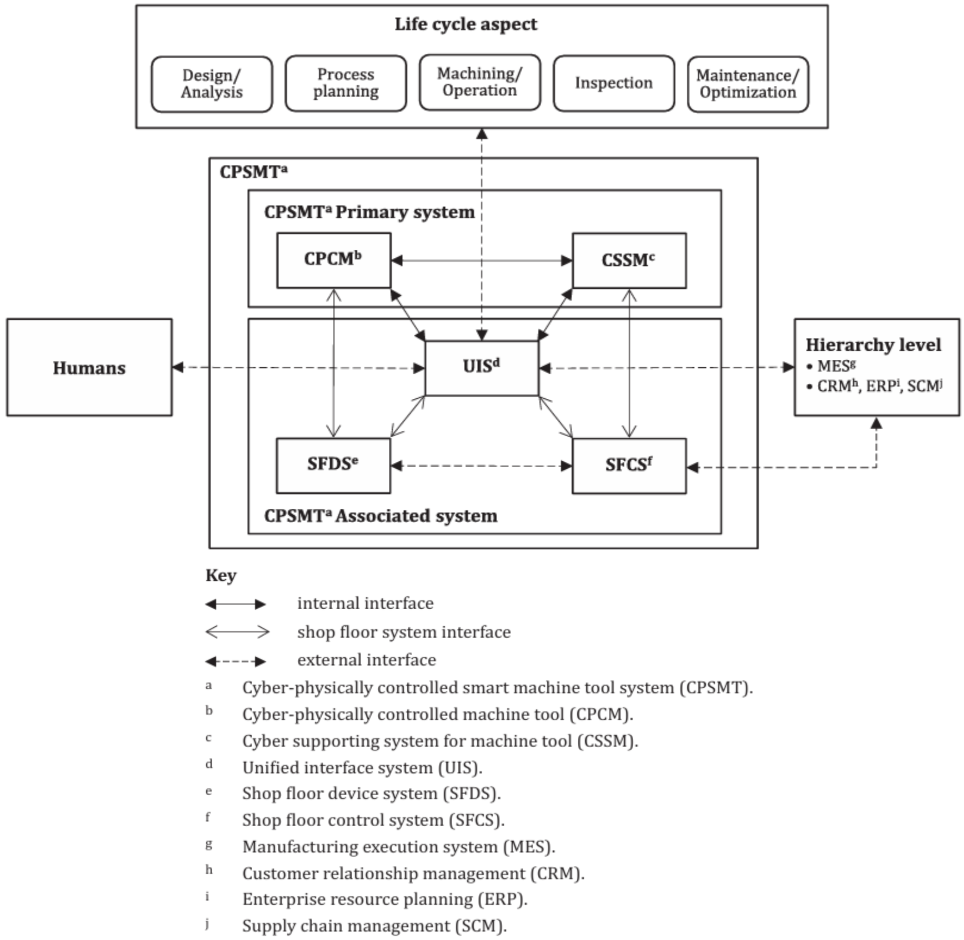


Figure 1 Reference Architecture ISO 23704

Figure 1 is the reference architecture provided by ISO 23704 for a CPSMT. A CPSMT should be capable enough to autonomously deal with machine tool abnormalities which can be done using big data, AI, Digital Twin with the help of Monitoring, Analysing, Planning and executing for the different conditions occure in a Machine tool. It should co-ordinate autonomously with various devices in the shop floor. It should have capability to collaborates autonomously with the shop floor control system (SFCS) in order to contibute to enhancing shop floor level operations KPI's e.g. production time, production quality, production cost etc.

As we can see in the reference architecture a CPSMT is divided into two parts

- CPSMT Primary system, and

- CPSMT Associated system

1.3.1. CPSMT Primary System

CPSMT is further broken into two components.

- Cyber Physically Controlled Machine tool (CPCM)
- Cyber Support System for a Machine Tool (CSSM)

1.3.1.1. CPCM

It is a machine tool that is operated using a Cyber-Physical control scheme, which adds more complex control functions to traditional machine control. It should create instructions for control to a machine based on data received from the machine's controller regarding the present progress of the machine or any parameter for which the controller may offer information about. There should be connection between CPCM and SFDS for better machine to machine collaboration.

1.3.1.2. CSSM

cyber-system that supports a physical system to enhance the performance of a physical system with monitoring, analysis, planning, and execution based on big data analytics / artificial intelligence, and digital twin. Cyber-supporting system for cyber-physically controlled machine tools (CPCMs) that provides decisions from the viewpoint of abnormality resolution and provides CPCM abnormality data to a shop floor control system and external systems including humans, life cycle aspects, and hierarchy level.

These are the two main aspects of any CPCM primary system that is described with the ISO 23704. Beyond this the machine should also have CPSMT associated system that is also further categorized in different sections as

- Shop Floor Device System (SFDS)
- Shop Floor Control System (SFCS)
- Unified Interface System (UIS)

1.3.2. CPCM Associated System

1.3.2.1. SFDS

A manufacturing facility that has set of devices for different operations on the shop floor. These include production machines that make the finished products, maintenance equipment that keep the production machines running, inventory system that tracks material and products and quality control etc.

1.3.2.2. SFCS

A cyber-system for a shop floor in order to increase and maintain the collaboration between different devices in a shop floor in order to track, schedule and can report on the progress of shop floor operations.

1.3.2.3. UIS

The primary system consists of a Cyber-Physically Controlled Machine tool (CPCM) and a Cyber-Support System for machine tools (CSSM).

ISO 23704 series further provides details about the CPSMT approach for different types of manufacturing processes such as Subtractive Manufacturing, Additive manufacturing into its further parts 2 and part 3. For this research the further discussion will be on the development of Cyber-Physically Smart Machine Tool system for Additive Manufacturing.

1.4. Additive Manufacturing

Additive manufacturing, commonly known as 3D printing, is another important component of Industry 4.0. Unlike traditional subtractive manufacturing processes, which involve cutting away material from a solid block, additive manufacturing builds objects layer by layer using digital design data.

The concept of 3D printing has its origins in early science fiction, notably in a 1945 short story by Murray Leinster using the pen name William Fitzgerald Jenkins. This story introduced the idea of a machine creating objects from magnetronic plastics, laying the foundation for what would become additive manufacturing. In the early 1970s, Johannes F. Gottwald filed a patent for a process involving liquid metal, **[7]** hinting at the potential for creating objects layer by layer, which is a key aspect of modern 3D printing.

Dr. Hideo Kodama's work in 1980 expanded upon Gottwald's idea **[8].** He suggested using thermosetting polymers and ultraviolet (UV) light to cure photopolymers, a precursor to today's stereolithography (SLA) technology. While Kodama's patent application in Japan didn't gain international traction, it marked a significant step forward in 3D printing development. Charles Hull's subsequent patent filing in 1986 for SLA technology led to the commercial release of the first 3D printer, the SLA-1, through his company, 3D Systems Corporation **[9].**

In the late 1990s and early 2000s, 3D printing began showing promise across various industries. But Adrian Bowyer's RepRap Project from 2005 was the initiative that really increased accessibility to 3D printing. **[9]**. To make the technology more accessible and inexpensive, the RepRap project set out to create a self-replicating device that could make the majority of its own parts. This effort culminated in the RepRap 1.0 Darwin machine, which could manufacture several of its essential components, democratizing 3D printing for enthusiasts, researchers, and small businesses.

The expiration of key patents, starting with Fused Deposition Modelling (FDM) in 2009, and followed by Selective Laser Sintering (SLS) and SLA in the 2010s, spurred significant growth and innovation in the additive manufacturing industry. With the removal of licensing fees, the barriers to developing and producing 3D printers decreased, leading to increased market competition and technological advancements. This trend drove the industry forward, fostering a dynamic ecosystem of companies striving to advance 3D printing technology.

In 2013, 3D Hubs was founded by Bram de Zwart, Brian Garret, and Filemon Schöffer. Initially, it served as an online platform connecting individuals needing 3D printing services with local printer owners **[10].** Over time, 3D Hubs evolved to meet the changing needs of the market, particularly as professional engineers began using the platform for product development. The company rebranded as Hubs and shifted its focus to connecting mechanical engineers with a network of manufacturing partners, offering a broader range of manufacturing capabilities to its users.

According to ASTM F2792-12 **[11]**, AM can be categorized as:

- **Vat Photopolymerization:** Vat photopolymerization involves a vat of liquid photopolymer resin that is selectively cured by a light source, typically a laser or UV light. This process includes technologies like Stereolithography (SLA) and Digital Light Processing (DLP). The light source traces the design in the liquid resin, solidifying the material layer by layer to form the final object. It is known for producing high-resolution and highly detailed parts, often used in applications requiring precision and smooth surface finishes.
- **Material Jetting:** Material jetting is similar to traditional inkjet printing but deposits droplets of build material instead of ink. The material, which can be a photopolymer or wax, is jetted onto the build platform where it is then cured by UV light. This process can create highly detailed and accurate parts with multiple materials and colours in a single build, making it suitable for prototyping and the production of complex geometries.
- **Binder Jetting**: Binder jetting involves the deposition of a liquid binding agent onto a powder bed, where it selectively binds powder particles together. This process can use a variety of materials including metals, sand, and ceramics. After printing, the parts typically undergo post-processing steps such as curing or sintering. Binder jetting is valued for its ability to produce large parts and for applications where full-colour printing is required, as well as for its potential cost-effectiveness in creating metal parts without the need for supports.
- **Material Extrusion**: Material extrusion, commonly known through technologies like Fused Deposition Modelling (FDM) or Fused Filament

Fabrication (FFF), involves the extrusion of thermoplastic material through a heated nozzle. The material is deposited layer by layer to build the part. This method is widely accessible and versatile, making it popular for rapid prototyping, hobbyist projects, and educational purposes. It is characterized by its simplicity, affordability, and the ability to use a variety of thermoplastic materials.

- **Powder Bed Fusion**: Powder bed fusion (PBF) encompasses a group of AM processes that use a laser or electron beam to selectively fuse powder particles in a powder bed. Technologies under PBF include Selective Laser Sintering (SLS), Direct Metal Laser Sintering (DMLS), and Electron Beam Melting (EBM). These processes are capable of producing highly complex and durable parts, often used in aerospace, automotive, and medical industries for end-use components. PBF is noted for its high precision and the mechanical strength of the parts produced.
- **Sheet Lamination:** Sheet lamination involves the bonding of sheets of material, which are then cut to shape to form the final object. Technologies such as Laminated Object Manufacturing (LOM) and Ultrasonic Additive Manufacturing (UAM) fall under this category. LOM uses adhesive-coated paper, plastic, or metal sheets that are laminated together, while UAM uses ultrasonic welding to join metal sheets. This method can produce large parts quickly and is relatively inexpensive, but the mechanical properties and resolution are generally lower compared to other AM processes.
- **Directed Energy Deposition**: Directed energy deposition (DED) utilizes focused thermal energy sources such as lasers, electron beams, or plasma arcs to melt materials as they are deposited. The material, which can be in powder or wire form, is deposited layer by layer to build the part. Technologies like Laser Engineering Net Shape (LENS) and Electron Beam Additive Manufacturing (EBAM) are examples of DED. This process is used primarily for repairing or adding material to existing

components and for creating large, complex metal parts with high structural integrity, often used in aerospace and defence industries.

These are the basic categorization of the AM process. Each of these additive manufacturing processes offers unique advantages and is suitable for different applications, contributing to the versatility and rapid growth of the AM industry.

This additive approach offers numerous advantages, including greater design flexibility, reduced material waste, and the ability to create complex geometries that are impossible to achieve with traditional manufacturing methods. As additive manufacturing technologies continue to advance, they They're set to revolutionize industries ranging from aerospace and automotive to healthcare and consumer goods. This is the reason why the manufacturing sector is started to understand the potential of the AM and is being investing in it.

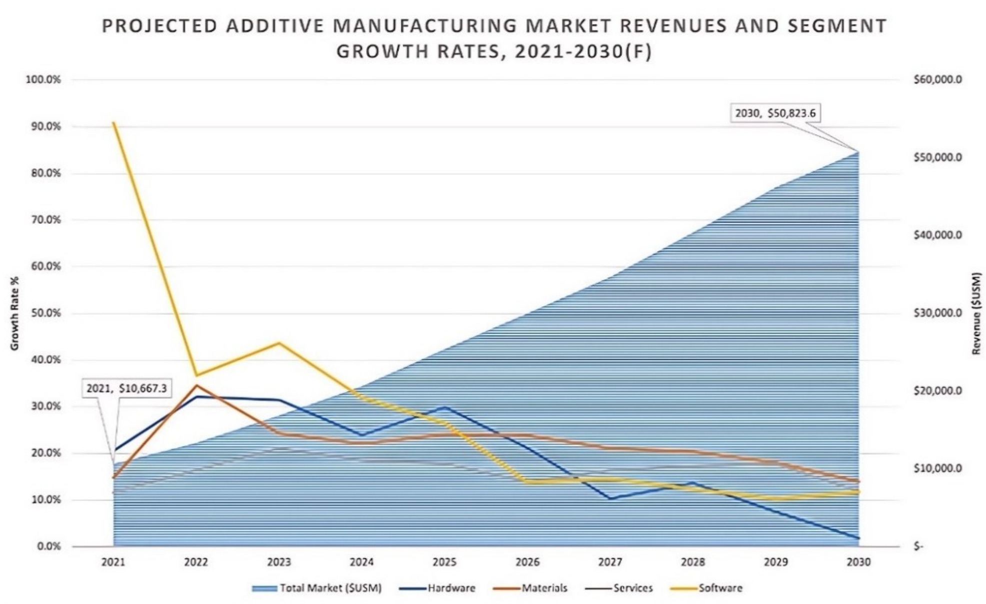
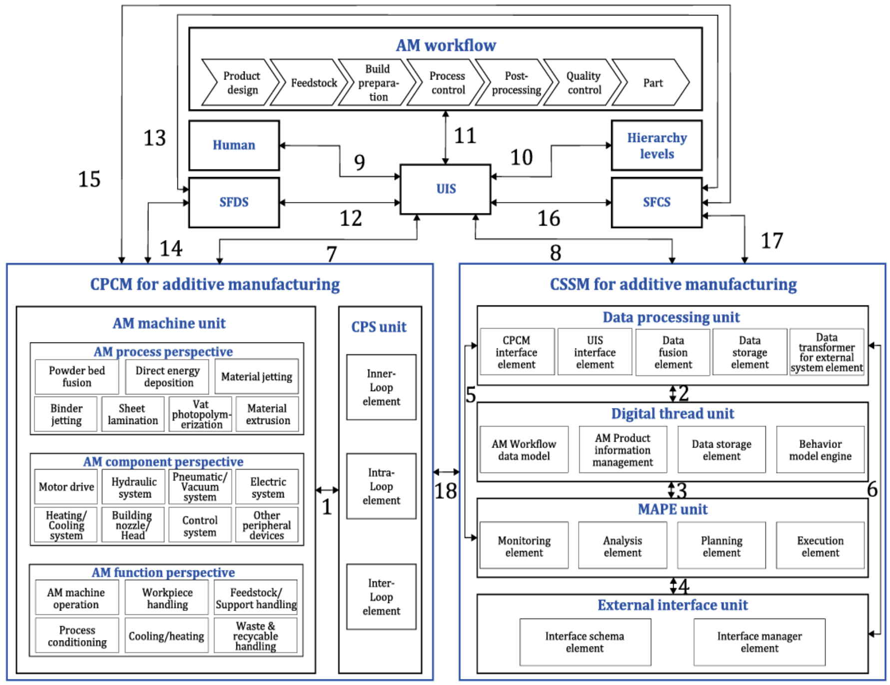


Figure 2 Trend in AM market share

According to Forbes **[13],** the AM sector reached $10.6 billion in revenue in 2021 and is expected to grow over $50 billion by 2030. So, the demand for Additive manufacturing will be growing on a large scale. The dynamic and layer-by-layer nature of additive manufacturing processes requires continuous monitoring to detect deviations and errors before time. Accessing the information about the product during the manufacturing phase might not be possible for all the conventionally available AM Machines. This is important in avoiding material loss and ensuring the production of high-quality components. Through the implementation of real-time monitoring systems, manufacturers gain the ability to track key process parameters, such as temperature, layer adhesion, product quality etc. to identify irregularities that may compromise the integrity of the final product. The application of in-situ error detection mechanisms further enhances the reliability of additive manufacturing processes. It involves monitoring and analysing data directly within the manufacturing environment, allowing for immediate response to potential errors. Advanced sensors and data analytics tools can be employed to detect anomalies, variations, or defects as they occur, preventing the production of faulty components. This proactive approach not only minimizes material wastage but also contributes to the overall cost-effectiveness and sustainability of additive manufacturing operations and provides valuable insights for continuous process improvement. Real-time process monitoring is important in the field of Additive Manufacturing. For that the AM system should be developed so that it can detect the anomalies and be "Smart".

1.5. ISO 23704 for Additive Manufacturing

ISO 23704 **[6]** provides a reference architecture for a smart AM machine in its documentation as shown in **Figure 3**. Here all the blocks from the **Figure 1** are broadly explained regarding the CPSMT for an AM system. The CPCM is divided into AMU and CPS for the Additive Manufacturing machine unit (AMU).



Key

1 data exchange between an AM machine unit (AMU) and a CPS unit
2 data exchange between a data processing unit and a digital thread unit
3 data exchange between a digital thread unit and a MAPE unit
4 data exchange between a MAPE unit and an external interface unit
5 data exchange between a data processing unit and a MAPE unit
6 data exchange between a data processing unit and a external interface unit
7 data exchange between a CPCM for AM and a UIS
8 data exchange between a CSSM for AM and a UIS
9 data exchange between a human and a UIS
10 data exchange between a hierarchy level and a UIS
11 data exchange between AM workflow and a UIS
12 data exchange between a SFDS and a UIS
13 data exchange between a SFCS and a SFDS
14 data exchange between a SFDS and a CPCM for AM
15 data exchange between a CPCM for AM and a SFCS
16 data exchange between a UIS and a SFCS
17 data exchange between a SFCS and a CSSM for AM
18 data exchange between a CSSM and a CPCM

Figure 3 Reference Architecture of ISO-23704 for Additive Manufacturing

1.5.1. AMU

The AMU is the physical system under consideration for monitoring and for which decisions are made regarding potential anomalies in order to improve the system's performance. According to ISO 23704 the AMU is characterized by three components

- AM Process Perspective
- AM Component Perspective
- AM Function Perspective

The process could be any of the 7 additive manufacturing methods that the ASTM F2792 has specified. The AMU will have different component depending upon its type such as Motor Drive, Hydraulic system, Pneumatic / Vacuum system, electrical system etc. and each of these components will have their specified function like AM machine operation, Workpiece handling, Cooling/ Heating etc. in an AM system which is why there are these blocks being shown in the reference architecture.

1.5.2. CPS

The CPS unit for CPSMT plays an important role in controlling and coordinating the AMU with the CSSM, SFDS, and SFCS. The CPS for AM should help the machine in autonomously dealing with abnormalities with the help of sensors, PLC's and CSSM for resolution of soft-real time abnormalities. According to ISO 23704 Soft-Real time means "Time-based operational characteristic in which processing of data by a computer in connection with another process outside the computer is degraded if results are not produced according to specified timing requirements".

To help the AMU with this the CPS should have.

- An inner-loop element
- An intra-loop element and
- An inter-loop element

The inner-loop element is the part of CPS which helps the machine to detect and solve the abnormalities for the machine tool in Hard-real time. According to ISO 23704 the definition of Hard-real time is "Time based operational characteristic in which processing of data by a computer in connection with another process outside the computer is incorrect if results are not produced according to specified timing requirements". For example, in a FDM machine the parameters that might severely affect the AM process can be layer height, print speed, bed temperature, nozzle head temperature etc. so these parameters should be monitored by the inner-loop element in real time in order to detect for any abnormal behaviour that might occur in the AM workflow.

The intra-loop element is the part of the CPS which helps the machine to generate the control instructions base on the data from the system in Soft-real time. The intra-loop element should receive command data form the CSSM regarding to confirm with the technical requirement in order to determine and analyse the status of the AM process.

The inner-loop element is the part of the CPS that helps the machine tool to collaborate with the different devices in the SFDS in order to have the machine-to-machine communication. Such as resource allocation or rescheduling of the shop floor devices, special requests from the manufacturing management, monitoring shop floor performance etc.

1.5.3. CSSM for AM

This is one of the important elements in a SAMS as all the analysis is supposed to be carried out in this section of the CPSMT the further division of CSSM can be seen in the **Figure 3** and is explained below

- Data processing Element (DPU)
- Digital Thread Unit (DTU)
- MAPE Unit (MAPE) and
- External Interface Unit

1.5.3.1. DPU

It is a set of functions to process the collected data which can be used for the further analysis as ISO 23704 states it should have

- CPCM interface
- UIS interface
- Data Fusion element
- Data Storage element and
- Data transformer for external entities element

The interface elements help the DPU with interfacing with CPCM and UIS in order to send and receive information with them. The CPCM will send or receive the information form the AMU controller or the Data collecting sensors that are being mounted on the AMU. The UIS will receive the data regarding the AM workflow from the DPU. Data Fusion element should help the SAMS in integrating the different data streams that are being sending the data to the CSSM for the analysis purpose so that the relevant information can be gathered about the process from it. Stages of the data preparation could be first to clean the data to remove the unnecessary noise then to format the data according to the requirement for analysis and then to transmit the data to the data storage unit. The data storage unit then stores the data which is used for analysis. It also should store the outputs from the analysis in order to share them whenever asked by any of the part in the system. This exchange of data should be done via a Data transformer for external entities element according to the format that the data is being asked for.

1.5.3.2. DTU

This unit should organize the data of AM workflow based on the data. This is one of the most important entities in the CSSM as it generates value-added key insights for the AM workflow consists of Product design, build-preparation, process control, post-processing, quality control. The DTU should consists of

- An AM workflow data model
- AM workflow data management
- AM behaviour model and
- Behaviour model engine

The AM workflow data model will describe the AM workflow. The data related to the product should be properly managed and organized. It could be the type of the workpiece design 3D model data either a STL, 3mf, AMF file etc, then it should store the information regarding the feedstock or supports that might be needed for the AM process. The information regarding preparation of the

Build process and setting of the parameters, Workpiece orientation, Support distribution etc should be well managed.

The work of AM workflow data management is to manage the data transmitted from the data fusion element and providing the in-process data to the required entities for the extraction of value-added information form the MAPE unit.

MAPE stands for Monitoring, Analysing, Planning, Executing. It does all of these activities based on the data for the enhancement of the KPI that are defined in the DTU. The output of the MAPE can be utilised for updating the AM workflow.

1.5.3.3. External Interface Unit

The task of this unit is to transmit the all the data generated by the DPU to SFCS and UIS in order to do the collaboration between the shop floor devices. Also to exchange the data with the humans which then can take several decisions for the AM process.

In this way the CPSMT for an AM machine can be developed.

AM has seen widespread adoption in the production of consumer goods due to its benefits in customization, speed, and material efficiency. Its ability to create complex designs without traditional Molds or tooling makes it ideal for manufacturing. This case study examines how AM has been integrated into production processes within the consumer goods sector, highlighting its impact on design innovation, manufacturing efficiency, and market responsiveness. Various examples demonstrate the successful implementation of AM, emphasizing its transformative effect on the industry.

1.6. Industry Examples

- Prusa, one of the leading manufacturers in the 3D printing industry, utilizes their own 3D printers to produce parts for their diverse range of products. Their 3D printing facility is equipped with more than 600 3D printers operating around the clock, 24 hours a day, seven days a week, throughout the entire year. The Prusa MK3S+ model requires approximately 22 hours to print all the necessary components for each printer. In contrast, the newer Original Prusa MK4 model significantly reduces this time, completing the same task in just 11 hours. Each month, Prusa's operations consume approximately 7200 kilograms of filament, reflecting the substantial scale of their production. The total printing time accumulated by the company's print farm is about 500,000 hours each month **[14].** This extensive operational capacity underscores Prusa's ability to maintain efficient and large-scale production. Given the high volume of printing, incorporating an effective print monitoring system would be crucial for Prusa. Monitoring systems are essential to minimize material loss and ensure consistent quality across such a large number of printers. By detecting and addressing issues in real-time, these systems would help prevent failed prints and reduce waste, enhancing overall efficiency.

- A3D is a manufacturing company specializing in on-demand 3D printing services, utilizing a diverse range of AM processes to meet varied customer needs. These processes include Fused Filament Fabrication (FFF), Selective Laser Sintering (SLS), Stereolithography (SLA) printing, and Jet Fusion, each offering unique advantages for different applications. **[15]** FFF is widely used for its cost-effectiveness and versatility, ideal for producing prototypes and functional parts. SLS is known for its ability to create durable, high-strength components without the need for support structures, making it suitable for complex geometries. SLA provides exceptional detail and smooth surface finishes, perfect for highly precise and intricate designs. Jet Fusion, meanwhile, excels in producing high-quality, functional parts at a rapid pace, suitable for both prototyping and end-use production. Given the variety of AM processes employed, incorporating a comprehensive quality monitoring system would be highly beneficial for A3D. Such a system would enable real-time tracking and control of the manufacturing process, ensuring consistency and reliability across different technologies. Quality monitoring can help identify and address issues promptly, reducing material waste and enhancing overall efficiency. For A3D, implementing advanced monitoring solutions would not only improve product quality but also optimize operational workflows, reinforcing their commitment to delivering high-standard, on-demand 3D printing services.

Some of the consumer goods are also being manufactured using AM processes. Here are some of the examples,

- Zellerfeld, a company that manufactures custom 3D-printed shoes. These shoes are made from thermoplastic polyurethane and are tailored to each customer's specifications. The company employs over 200 custom-made 3D printers in their production process, allowing for precise customization according to individual orders.**[16]**
- Stubby Nozzle Co. makes custom nozzles for different nozzle heads for different leaf blowers using Additive manufacturing processes. **[17]**
- The Wilson Airless Prototype basketball is made with a 3D-printed polymer lattice structure designed to mimic the performance of a traditional basketball. The ball features eight panel-like lobes and a familiar seam structure, with hexagonal holes across the surface that allow air to pass through freely, reducing its weight.**[18]**

And there are many more examples where the AM processes are being incorporated for large production of consumer goods. As the demand for AM production increases, the need for monitoring the production process will also increase as the processes are still very costly and the loss of time and material can affect further the cost of final print.

1.7. Organization of the Thesis

This thesis is consisting of six chapters. Current chapter provides an introduction and background to the research topic, highlighting its importance, defining key concepts, and outlining the scope of the study. This chapter will also give a brief overview of the subsequent chapters.

The second chapter will focus on conducting a comprehensive literature review, critically analysing and synthesizing existing research related to the topic, identifying gaps in current knowledge, stating the research problem and objectives and discussing relevant theories and frameworks.

The third chapter will explore into the methodology employed in the research, describing the research design, data collection methods and data analysis procedures.

The fourth chapter will provide a detailed explanation of the development process undertaken, including the steps involved in designing, implementing and creating the research output, highlighting innovative aspects of the process.

In the fifth chapter, the results and findings obtained from the research will be presented, utilizing appropriate data visualization techniques, analysing and interpreting the results in relation to the research objectives, and comparing them with previous studies or literature.

Finally, the sixth chapter will summarize the main conclusions and contributions of the research, discuss its potential areas for future research, provide recommendations for further investigation, and reflect on the overall research experience and lessons learned.

Chapter 2 Problem Formulation

In this chapter, we will examine the integration of CPS in additive manufacturing. The focus will be on reviewing current progress in real-time monitoring, data analytics, and automation within AM processes. This literature review aims to provide a comprehensive overview of the current state of CPS in AM and its implications for manufacturing practices.

2.1. Literature Review

We will now go through the literature that is currently available for additive manufacturing process monitoring. Keywords such as Fused Deposition Modelling (FDM), Fused Filament Fabrication (FFF), Additive Manufacturing (AM), Fault Detection, Digital Twin (DT), Cyber-Physical Systems (CPS), Product Lifecycle Management (PLM) were used for the search of the literature.

[19] introduces an approach to enhance 3D printing processes through a collaborative cloud-edge architecture, leveraging the concept of digital twins. Researchers have created a digital twin information model for 3D printers and discussed essential technologies for real-time monitoring and collaborative control at the cloud-edge interface. Through a case study, the paper demonstrates the development of an edge platform utilizing Three.js for digital twin modeling, along with cloud-based 3D printing services for collaborative purposes.

[20] This study presents the development of a digital twin ecosystem (DTE) for testing, monitoring, and managing an AM FDM machine in a virtual environment. The DTE replicates the machine's operation and performance for in-process analysis and optimization. It consists of two main components: the data acquisition-processing-distribution component (APDC) and the virtual-representation component (VRC). The DTE's capabilities were verified and validated using sensor data, assessing various machine parameters such as extruder position, temperature, and speed.

[21][20] This research introduces a framework for monitoring and optimizing FDM parameters using Digital Twin and Cloud technologies. The framework, implemented as a mobile app, allows engineers to conduct offline and online simulations. It includes AR-based immersive interfaces for remote machine operation and monitoring. After each process, engineers manually assess the quality of components, storing results in a Cloud database for future reference. Users can review historical assessments to optimize parameters and receive recommendations based on past results.

[22] This study introduces Deep Learning technique for monitoring abnormalities in FDM 3D printers. They have developed a system which monitors an FDM machine for its surrounding temperature, humidity and print bed temperature for any faults that might arise due to fluctuations of these parameters. They have proposed a Lightweight convolution neural network to detect faults from the sensors that are attached to the machine.

[23] This paper presents an improved fault diagnosis approach for FDM processes using Acoustic Emission (AE) sensors. The AE during production is dependent on many of the machine parameters such as Print Speed, Feed Rate, Print Acceleration etc. AE hits from different extruder states are obtained, and time-and-frequency-domain features are extracted for real-time FDM machine monitoring, particularly for extruder health.

[24] This study introduces a multi-camera sensing system and method to detect catastrophic failures during 3D printing process. It compares real-time images of the print bed with images generated from the design file. However, this technique has an important limitation about part concavity; any part geometry that is hidden from the camera view cannot be monitored with this technique, which might result in undetected deformations of the part.

[25] This paper outlines an architecture utilizing IoT technologies to acquire, transmit, and store sensor data for a digital twin in manufacturing processes. A deep learning-based CNN classifier detects patterns leading to defective products, particularly identifying vibration patterns using integrated LSM330 accelerometer and gyroscope during the printing process.

[26] This work proposes a method for in-process monitoring of part geometry in fused filament fabrication (FFF). The method addresses key challenges in current optical imaging techniques, such as balancing resolution and coverage needs, handling complex and challenging optical conditions in the production process, and accurately assessing part quality during fabrication using reference geometry from CAD models, which often poorly represent the actual FFF process characteristics. The researchers used a microscope which traversed through the edges of every printed layer in order to monitor the print quality.

This leads us to the conclusion that the characteristics of an AM process, such as nozzle head position, nozzle temperature, bed temperature, print speeds, and acceleration, are some of the most important variables that might affect the final product's quality.

2.2. Research Gap

a. Integrating with existing Product Lifecycle Management (PLM) systems and other manufacturing software tools is complicated. This complexity arises from differences in data formats, communication methods, and software designs. Making these systems work together requires advanced data conversion and alignment processes. Additionally, various software tools in the manufacturing environment use different communication methods, needing middleware to translate and transfer data effectively. As a result, seamless integration with commonly used software and data sources is often missing.
b. The research literature mentioned above, which focuses on the development of Cyber-Physical Systems for FDM machines, does not primarily concentrate on the quality monitoring of the actual printed components. As a result, there is a noticeable gap in addressing the critical issue of ensuring and maintaining the quality of the printed

parts during and after the manufacturing process. This lack of focus on quality monitoring can lead to inconsistencies and defects in the final products, underscoring the need for more research in this area.

c. Specifically, in the case of FDM additive manufacturing, an object printed at one position might not be the same as one printed at another position due to the inherent nature of the process. Variations in temperature, material flow, and machine calibration can lead to differences in the final product. Additionally, since parts are built up layer by layer, it becomes challenging to validate the internal geometries of an item once printing is complete. This makes it difficult to ensure that the internal structures are accurate and free from defects, which is crucial for the overall quality and performance of the printed component.

d. Conventionally available FDM printers lack the capability to provide real-time access to information about the product during the manufacturing phase. As a result, operators have limited visibility into the ongoing manufacturing process and are unable to monitor the quality and progress of the print in real time. This lack of accessibility to critical manufacturing data hinders the ability to detect and address issues as they arise, leading to potential defects or inconsistencies in the final product.

2.3. Research Objectives

a. Developing a tailored Data Collection System for FDM printers, incorporating a robust mechanism for data acquisition and analysis. This system will efficiently gather and process printer performance metrics, enhancing overall operational insight and optimizing printing processes.

b. Implementing in-situ monitoring for FDM printing, enabling precise tracking of geometric variations resulting from mechanical movements. This approach ensures real-time detection and analysis of printing anomalies, facilitating proactive adjustments to optimize print quality and process efficiency.

c. Using open-source technologies so that the implementation can be replicable.

d. Standardization of the developed platform with ISO 23704 ensuring accessibility, efficient performance, and replicability.

Chapter 3 Proposed Methodology

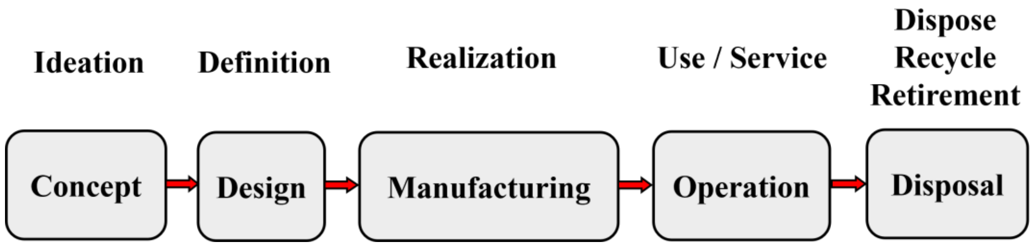


Figure 4 Product Lifecycle Management workflow.

3.1. Product Lifecycle Management

PLM concept revolves around five phases as - Ideation, Definition, Realization, Use / Service and Disposal / Recycle / Retirement. The product goes through several stages in each of these five phases **[27].** In the initial stages, the product is simply an idea, a concept that has not been developed yet. As it progresses into the definition phase, these ideas are converted into a detailed description, outlining what the product will be and how it will function. By the end of the realization phase, the product exists in its final form, such as a car, ready to be used by customers. During the use/service phase, the customer has the product and is actively using it. This phase involves the product performing its intended functions and may include support and maintenance services to ensure it operates correctly. During this time, the product serves its purpose, and the customer relies on it for its designed utility, interacting with it. Eventually, the product reaches a stage where it is no longer useful or functional. In this final phase, the product is retired by the company and disposed of by the customer. Disposal can involve various methods, including recycling by the customer, the company, or a third party. This phase ensures that the product is responsibly managed at the end of its life cycle, reducing waste and potentially reclaiming materials for future use.

PLM brings together many separate processes, areas of expertise, functions, and applications that were previously independent. Despite focusing on the same product, each of these had their own terminology, rules, culture, and language. It integrates them all into a single system. Organizations can use

PLM to manage products consistently and in a unified way throughout their entire lifecycle. This approach ensures that all aspects of the product are addressed together, rather than separately. It creates a seamless and continuous process for product management.

By uniting all product-related issues under one system, it allows for a more coherent and coordinated approach. With this, all product data, processes, and stakeholders are integrated into a centralized system. This enables better collaboration, data sharing, and a more holistic view of the product throughout its entire lifecycle, from concept to retirement.

The approach of integrating PLM can be utilized for a wide variety of products and processes. This versatility makes it a valuable tool in various industries and applications. In this research, we are focusing on the application of the PLM approach within the context of the AM process.

When Additive Manufacturing is deployed in a production environment, it will present unique challenges and opportunities. The integration of PLM with AM can significantly enhance the efficiency and effectiveness of the manufacturing process. PLM provides a structured framework that manages the entire lifecycle of a product, from the initial design through to its eventual disposal. This structured approach can be particularly beneficial for AM due to its intricate nature and the precision required in its processes.

We developed a Data Collection System for the AM process. This system can collect and analyze data continuously throughout the manufacturing process. This real-time monitoring is crucial for identifying and addressing issues as they arise, ensuring that the production process remains consistent and meets quality standards.

For instance, during the AM process, various parameters such as Nozzle tool head position, speed, acceleration, layer thickness, and material usage are critical to the quality of the final product. The data collection systems can track these parameters, comparing real-time data against predefined standards and baseline error patterns. Any deviations from these standards can be quickly identified and rectified, minimizing defects and improving overall product quality.

We facilitated a comprehensive error analysis and quality control process for Additive Manufacturing. By establishing a baseline error pattern from the standard component, we can analyze the potential issues when they occur. This capability allows for proactive measures to be taken, reducing the likelihood of errors during the manufacturing process and the loss of material can also be avoided.

In the context of Additive Manufacturing, error analysis might involve examining the consistency of layer deposition, the adherence of materials, and the structural integrity of the printed components. The collected data can help us analyze, providing insights that help optimize the AM process. This level of detailed analysis is essential for maintaining the high precision required in AM.

Beyond monitoring and error analysis, PLM plays a vital role in managing the entire lifecycle of products created through Additive Manufacturing. This includes the initial design phase, where digital models are created and optimized for printing, as well as the production phase, where these models are brought to life.

Throughout the lifecycle, PLM systems ensure that all aspects of the product development and manufacturing processes are integrated and aligned. This integration leads to continuous improvement, as data from each stage of the lifecycle can be used to refine and enhance subsequent stages. For example, insights gained from the operation and performance of a printed product can inform future design iterations, leading to better and more efficient manufacturing processes.

The integration of PLM with Additive Manufacturing will offer a comprehensive approach that enhances the efficiency, quality, and effectiveness of the AM process. By leveraging PLM systems for real-time monitoring, error analysis, and lifecycle management, manufacturers can optimize their AM operations, resulting in superior products and more efficient production workflows. This research highlights the potential of PLM to transform Additive Manufacturing into a more dependable and productive technology, reinforcing its value across various applications and industries.

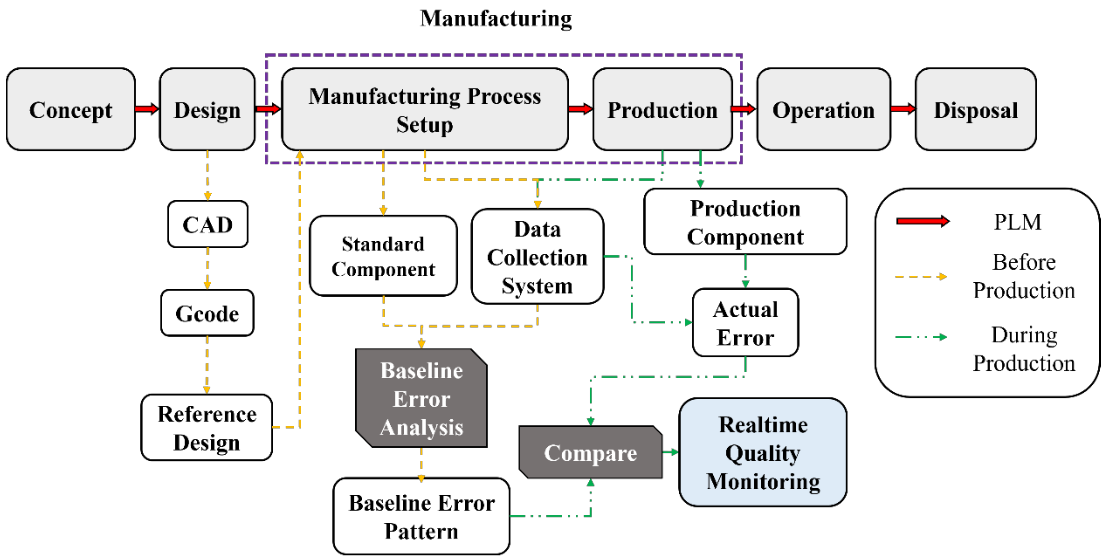


Figure 5 Proposed Methodology

3.2. Cyber-Physical PLM Environment

demonstrates novel approach of this research as the integration of PLM with the AM manufacturing process. It covers the entire lifecycle of a product, from the initial concept stage to its final disposal. It highlights how PLM unifies various stages and incorporates error analysis and quality monitoring during production. The focus of this research will be more on the manufacturing aspect of the PLM process for the AM.

The Process of AM is divided into several distinct stages: Concept, Design, Manufacturing Process Setup, Production, Operation, and Disposal. These stages represent the product lifecycle, with arrows indicating the flow of information and processes between each stage.

The lifecycle begins with the Concept phase, where the idea for the product is first conceived. This stage involves high-level planning and defining the product's purpose, requirements, and overall goals. It is a critical phase where initial decisions shape the direction of the product development process.

Following the Concept phase is the Design phase. During this stage, the product idea is translated into detailed designs. The tools and processes involved in this phase include Computer-Aided Design (CAD), which is used to build three-dimensional models and technical illustrations. CAD helps in visualizing the product and creating accurate specifications that will guide the manufacturing process. The output from the CAD designs is often translated into Gcode, a language used to control automated machine tools and machinery during production. This will be our reference design, serving as a benchmark of the desired product for the manufacturing process to produce. This ensures that the designs are consistent and meet the necessary standards. The transition from the Concept phase to the Design phase is marked by a red arrow, indicating the involvement of PLM. This ensures that the conceptual ideas are accurately translated into detailed design specifications, maintaining consistency and coherence.

The next stage is the Manufacturing Process Setup, where preparations for the actual production take place. This phase involves setting up the necessary processes and components required for manufacturing our reference design. One key aspect of this phase is the establishment of standard components. This will be a predefined, standardized part that will be used in the production process to ensure uniformity and quality. Another critical activity during the Manufacturing Process Setup is Baseline Error Analysis. This step involves identifying potential errors before production begins. As for any production process even if it is perfect there will be some inherent errors that might be there in the process which will be reflected in the final product. By analyzing the data from the data collection system, a baseline error pattern is established. This pattern serves as a reference for comparing actual errors during production, helping in predicting and mitigating potential issues.

The activities before production, such as CAD, Gcode generation, reference design, standard component setup, and baseline error analysis, are represented by yellow dashed arrows. These arrows indicate the preparatory steps taken to ensure that the production process is smooth and efficient, minimizing the likelihood of errors.

The Production phase is where the actual manufacturing of the product occurs. This stage is crucial as it transforms the designs and preparations into a physical product. During production, continuous monitoring and adjustment are necessary to guarantee the output's quality. A Data Collection System is employed to gather real-time data from the production process. This system monitors various parameters and collects information during manufacturing. Here we are monitoring the nozzle tool head position during the manufacturing process of the FDM machine. Further details on this will be explored in the next chapter.

Actual errors that occur during production are identified and recorded. These errors are then compared against the baseline error patterns established during the Manufacturing Process Setup. This comparison helps in identifying deviations and understanding the root causes of any discrepancies. The green dashed arrows in the diagram represent these activities, highlighting the continuous monitoring and quality control measures taken during production.

Real-time Quality Monitoring is a critical component of this phase. It involves continuous observation and assessment of the production quality. This process ensures that any issues are detected promptly and addressed immediately, maintaining high standards of quality throughout the manufacturing process.

A machining process inherently includes some types of errors no process is perfectly flawless. To reduce these errors, we need to optimize the process parameters. According to our proposed methodology from **Figure 5**, the first step in this analysis is optimizing these parameters to create a baseline error plot.

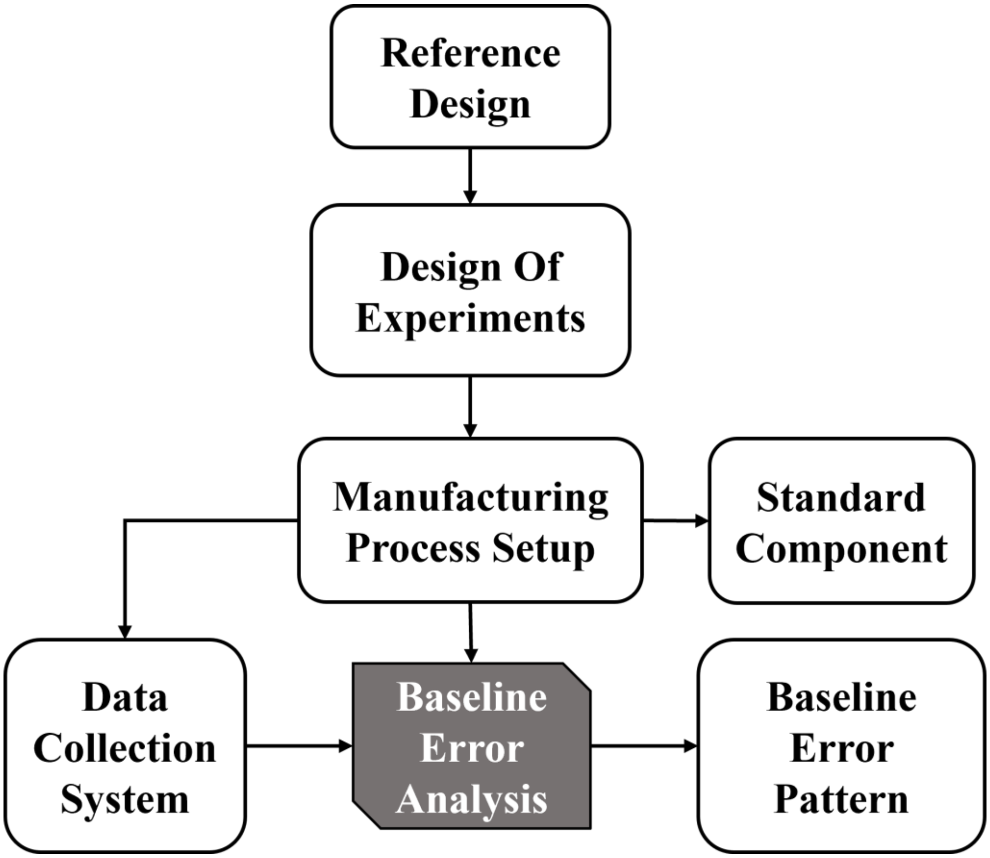


Figure 6 Baseline Error Pattern

The optimization process will vary based on several factors, including the type of product, the acceptable tolerance levels, the print time, material requirements etc. The manufacturer must conduct a thorough analysis of these factors to determine the optimal process parameters for the specific product. This involves evaluating different settings and conditions to find the best combination that minimizes errors while meeting production goals.

Once the optimal parameters are identified, the product is manufactured using these settings. The error plot generated during this phase represents the baseline error pattern. This pattern is crucial as it acts as a benchmark for the machining process. For prismatic structures, the baseline error pattern is expected to be a straight line, indicating uniformity and consistency in the structure along the extrusion direction. This straight line suggests that the cross-sectional shape and size remain constant, leading to predictable and linear errors along the Z-axis. In contrast, for non-prismatic structures, the shape of the baseline error pattern varies according to the type of cross-section that changes along the Z direction. Since the cross-sectional dimensions or geometry differ at various points along the height, the errors introduced during manufacturing or analysis will also vary. These variations depend on the specific changes in the cross-section, resulting in a more complex error pattern that reflects the changing structure. Further details can be found in **Chapter 5**. By comparing the error patterns of newly produced parts to this baseline, manufacturers can assess the quality and consistency of the production process. The baseline error pattern thus serves as a standard for ensuring that the produced parts meet the desired quality and performance criteria. This systematic approach helps in maintaining high standards in manufacturing, allowing for continuous monitoring and improvement of the machining process. It ensures that any deviations from the baseline can be quickly identified and addressed, leading to higher quality products and more efficient production processes. Once the baseline error plot is developed. The next phase is to do the comparative analysis of the new manufactured product with the standard product which was manufactured with the standard settings.

For comparison of the currently manufacturing product with the reference product for in-layer analysis is the next stage in the monitoring process. We get the reference information about the product from the designing stage is termed as reference design here. For an FDM AM process, the Gcode file provides the information about the reference design which has the information about the final product to be made. By parsing the gcode, we get the information about the manufacturing process, process parameters and mainly the nozzle tool head position during the manufacturing process which is the main focus of this study. By comparing the actual tool head position that we get from the DCS with the reference position which we get from the reference data, the deviation or the error in the tool head position can be calculated. By doing this analysis Layer-by-Layer, we can monitor the progress of the AM process and also keep monitor the quality of the process. The process flow of calculating the error within the layer is explained with.

To do the actual error calculation, let's say for layer number 1, first we get the reference data from the gcode about the motion of the tool head throughout the layer 1. Then once the layer 1 is deposited by the FDM machine the DCS will provide the actual tool movement during the deposition process for that layer. Now we have two point clouds associated with the reference data and actual measured data. The desktop FDM machines set their home before every print but the homing of each of the axis might induce some error due to incorrect homing so for our calculation the matching of the two point clouds of reference data and measured data is necessary. Here we are using an Iterative Closest Points (ICP) approach for aligning the two-point clouds. Iterative Closest Points is a widely utilized algorithm in the field of computer vision and 3D shape analysis, primarily for aligning two-point clouds. The process involves iteratively refining the transformation comprising rotation, translation, and scaling that minimizes the distance between corresponding points in the source and target point clouds. Initially, the algorithm selects the closest points in the target cloud for each point in the source cloud. Subsequently, it computes the optimal transformation to align these point pairs and updates the point correspondences based on the transformed source cloud. This iterative process continues until convergence, typically when the change in alignment error falls below a predefined threshold. ICP is crucial for applications such as 3D modelling, object recognition, and medical imaging, where precise alignment of point clouds is essential for accurate analysis and interpretation of data. Despite its robustness, ICP can be sensitive to initial alignment, noise, and outliers, necessitating the use of enhancements like point cloud preprocessing in order to improve performance and accuracy. Here we are doing an ICP process for aligning the measured data with reference data in order to find the closest points. ICP aligns the points clouds by translating and rotating the target point cloud with source point cloud such that the change in the total distance between the corresponding points is below a predefined threshold.

To increase the analysis speed, the two point clouds which are of reference data and measured data are matched with each other with their corresponding centroids. First the centroids for both the point clouds are calculated and then the measured data point cloud is translated to the reference data point cloud. After this step the ICP is used in order to align the two point clouds.

Once the two point clouds are aligned with each other than the further analysis of finding the closest points starts. A python script is used for this in which a function called `find_closest_points` is designed to determine the nearest corresponding points in a dataset of measured data for each point in a reference dataset and to quantify the alignment between these two datasets. It begins by constructing a KD tree from the measured data, which is a data structure optimized for efficient nearest-neighbour searches in multi-dimensional space. This tree is then queried for each point in the reference data to find the closest point in the measured data, resulting in an array of indices that indicate these nearest neighbours. Using these indices, the function extracts the closest points from the measured data corresponding to each reference point.

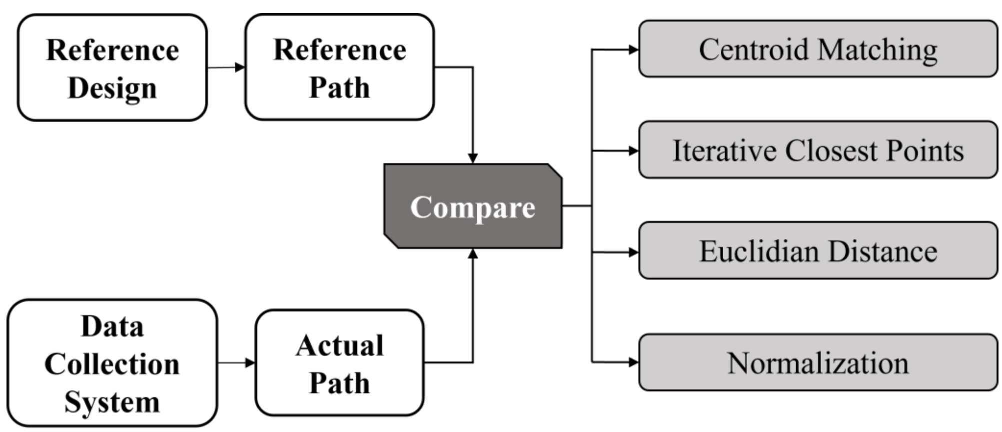


Figure 7 In-Layer Analysis

The Euclidean distances between each pair of reference and closest measured points are then calculated, which represent the errors between the each of the points in the two datasets. The function proceeds to compute the average of these distances to provide a measure of the typical error, and the standard deviation to indicate the variability of these errors. Finally, the function returns the array of closest points from the measured data, allowing further analysis between the reference and measured data.

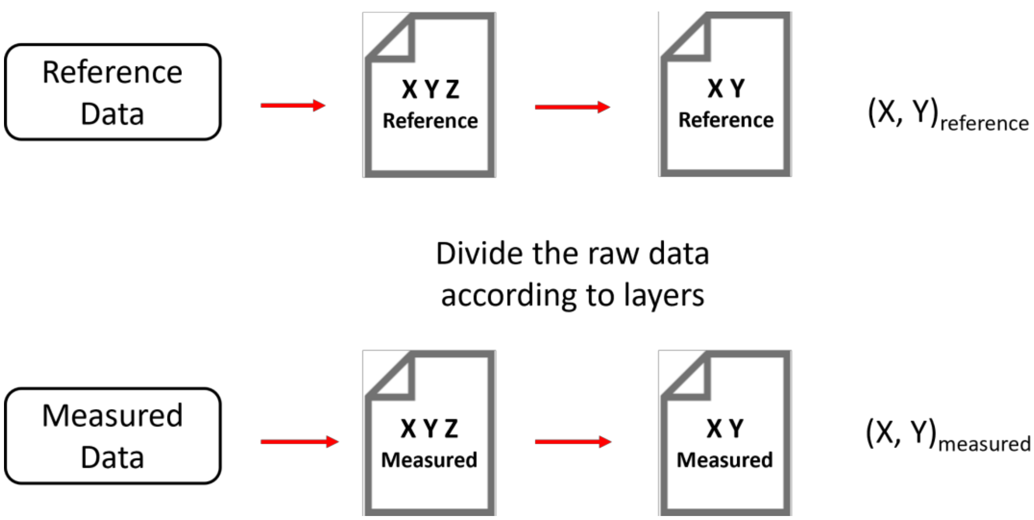
Mean Error for a Layer

$$\text{Error}_{\text{layer}} = \frac{\sum_{i=1}^{n} \sqrt{(X_{ref} - X_{mea})_i^{\,2} + (Y_{ref} - Y_{mea})_i^{\,2}}}{n}$$

Standard Deviation of Errors for a Layer

$$\sigma(\text{Error})_{\text{layer}} = \sqrt{\frac{\sum_{i=1}^{n} (Error_i - (Error_{layer}))^2}{n}}$$

n: Number of points in the layer



In this way, the error in the movement of the nozzle tool head is calculated for a single layer, and this process continues for each layer during the production process. This approach helps us identify the error pattern and compare the developing component with the standard component. By analysing the errors layer by layer, we can gain a detailed understanding of how the production process affects the final accuracy of the part.

Once the average error is calculated, the error values are normalized to ensure consistency in our analysis. Normalizing the data means putting all the error measurements on the same scale, which is crucial for accurately comparing errors across different layers during the production process. By standardizing the error values, we can effectively identify any patterns or trends in error accumulation as each layer of the component is manufactured. This systematic approach allows us to identify minor details in error distribution and helps us pinpoint specific stages where errors may be More prominent. Additionally, normalizing the error data enables us to make a direct comparison between the developing part and the standard one, providing valuable insights into the discrepancies that arise during production. Analysing errors layer by layer not only offers a comprehensive understanding of how the production process impacts the final accuracy of the part but also allows us to track the evolution of errors throughout the manufacturing process. Additionally, utilizing normalized data makes it simpler to comprehend and discuss our results, assisting in conveying insights to stakeholders and decision-makers. This careful approach to analysing errors and standardizing data can also guide practical improvements in manufacturing methods, leading to better quality and accuracy in the end products.

The use cases of the developed Data Collection System are as below:

1. Error Monitoring for the Process

One of the primary advantages of this data collection system is its ability to monitor errors throughout the manufacturing process. By continuously collecting data, the system can detect anomalies or deviations from the standard operational parameters. This real-time error monitoring allows for immediate corrective actions, reducing the likelihood of defective products and minimizing downtime and material loss. Early detection of errors can also prevent more significant issues from developing, saving both time and resources.

2. Localization of Errors

In addition to identifying errors, the system excels at pinpointing the exact location where an error has occurred. This localization capability is crucial for efficient troubleshooting. When an error is detected, the system can provide detailed information about the specific stage or component of the manufacturing process that is affected. This targeted approach helps users quickly address the issue without needing to inspect the entire process, leading to faster resolution times and less disruption to production.

3. Speed and Acceleration Analysis

The data collection system also enables comprehensive analysis of speed and acceleration within the manufacturing process. By monitoring these parameters, manufacturers can gain insights into the dynamic aspects of their operations. This analysis is important for several reasons:

- Product Development: Understanding the speed and acceleration patterns helps in developing products that can withstand the operational stresses of the manufacturing process. It ensures that new products are designed with the right specifications to meet performance standards.
- Determining Optimal Parameters: Analysing speed and acceleration data allows for the identification of optimal operating conditions. This information can be used to adjust the process parameters to achieve the best possible performance, leading to improved product quality and consistency.
- Process Design and Optimization: With detailed data on how different speeds and accelerations affect the manufacturing process, engineers can design more efficient and effective processes. This can involve tweaking existing processes or developing entirely new ones that optimize productivity and minimize waste.

After the production phase, the product enters the operation phase. This phase involves the actual use of the product by end consumer or its integration into larger systems. The operation phase is crucial for gathering feedback and understanding the performance of the product in real-world conditions.

The final stage in the product lifecycle is Disposal. This phase involves the responsible retirement and disposal of the product once it has reached the end of its useful life. The Disposal phase ensures that Products are disposed of in an environmentally friendly way, following regulatory standards and minimizing environmental impact.

PLM plays a key role throughout the entire process, integrating all stages from concept to disposal. By unifying these stages, PLM ensures a cohesive and consistent approach to product development and management. One of the key benefits of PLM is its role in error monitoring. By involving baseline error analysis and real-time quality monitoring, PLM helps identify and rectify errors promptly, ensuring the production process remains efficient and of high quality.

Moreover, PLM facilitates the seamless flow of data across different stages. Information collected during each phase is utilized effectively to improve the overall product lifecycle. This continuous data flow ensures that every stage of the product lifecycle is informed by insights from previous stages, leading to better decision-making and improved product quality.

Chapter 4 Cyber-Physical Production Environment Development

In this chapter, we will outline the development process of the Smart Additive Manufacturing System (SAMS). To create a proof-of-concept, we chose the material extrusion additive manufacturing process due to its versatility and widespread adoption. Our initial step involved selecting an AMU and identifying the specific parameters necessary for monitoring this unit.

Through an extensive literature review, we determined that several factors, including the position, speed, and acceleration of the nozzle tool head, significantly influence the quality of products produced using additive manufacturing methods. Considering the significance of these parameters, we decided to focus our efforts on monitoring the nozzle tool head position. This parameter is crucial as it directly impacts the precision and accuracy of the manufacturing process, thus affecting the final product's quality. By accurately tracking and analysing the nozzle tool head position, we aim to ensure the consistency and quality of items produced through additive manufacturing techniques.

Our initial work involved the MCube 3D Guider 200, which features lead screw-driven axes for the nozzle head movement. To select an appropriate sensor for measuring the nozzle head position, we selected a list of potential sensors, including the Ultrasonic Sensor, Infrared Sensor, and Rotary Encoder.

Table 1 Sensors Selected for Experiment

Sensor	Measurement Type	Model
Ultrasonic Sensor	Time-of-Flight	HC-SR04
Infra-red Sensor	Time-of-Flight	Sharp 2Y0-A21
Optical Encoder	Rotary Position	Orange 600ppr Rotary Optical Encoder

IR Sensor

Optical

Rotary

Encoder

Ultrasonic

Sensor

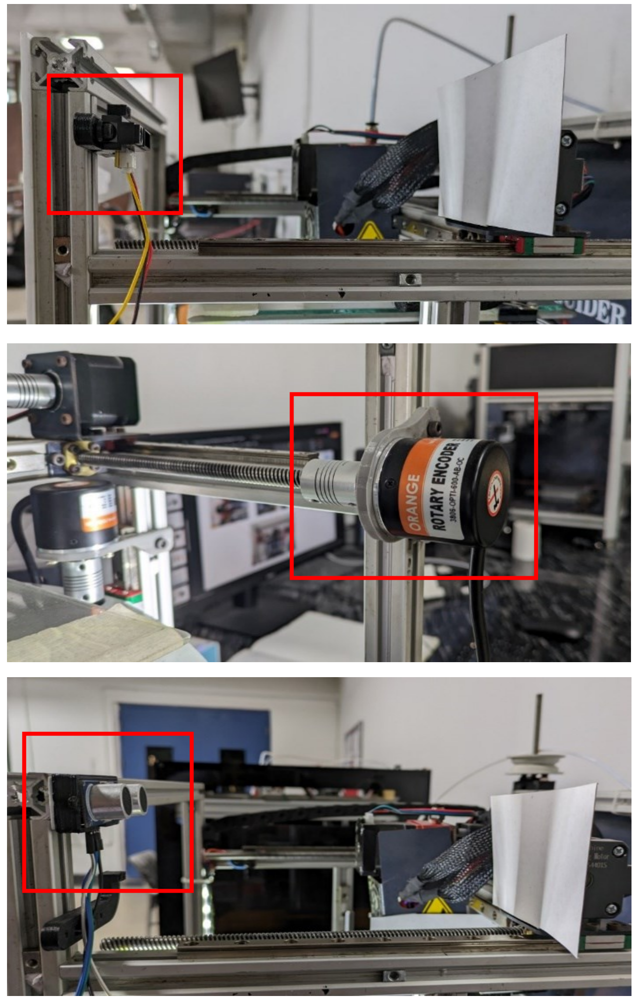
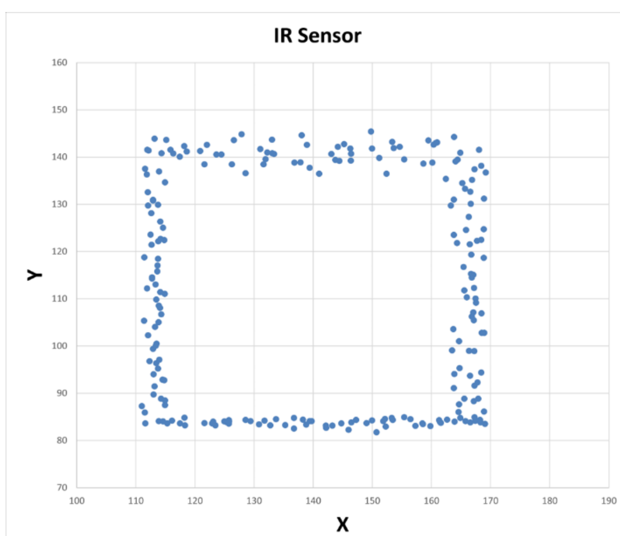
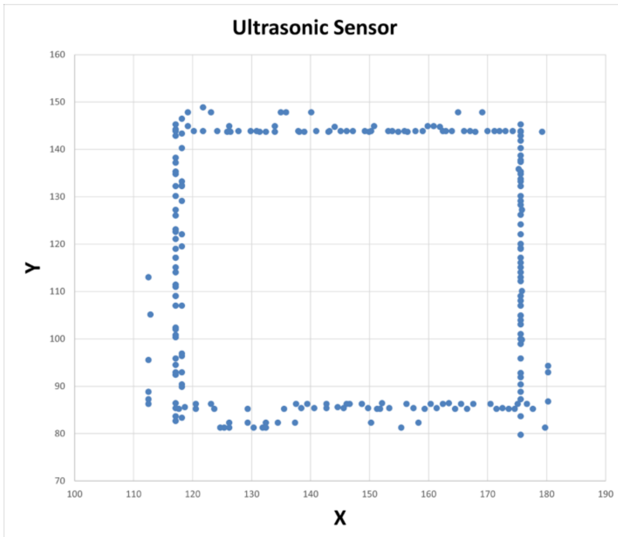
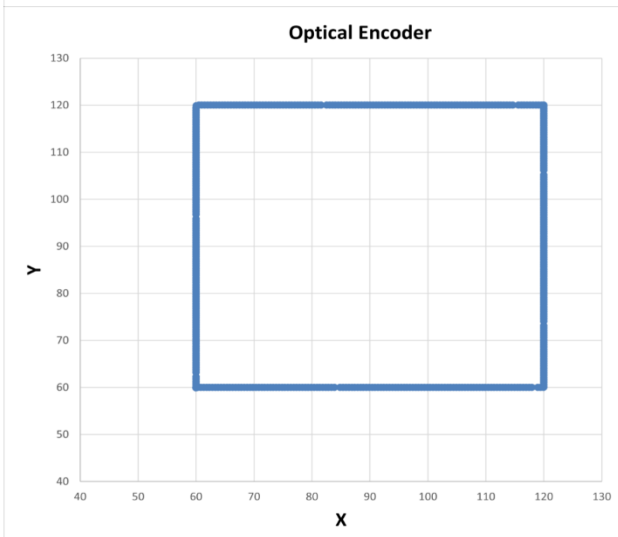


Figure 8 Implementation of different Sensors

To evaluate the accuracy of these sensors for position measurement, we created a test setup for each sensor to monitor the X and Y axis of the tool head. The







test was to move the tool in a square shape with sides of 60mm and the results were as below

As can be seen in the plots, the infra-red sensor had the worst traceability among the three sensors tested. Its output was with very high noise levels and inconsistent data, making it unreliable for precise measurements. The Ultrasonic sensor performed moderately, but it still showed some variability and occasional drift in the data. In contrast, the optical encoder demonstrated the best traceability, consistently providing accurate and reliable data with minimal noise and high repeatability. Given its superior performance in terms of accuracy and reliability, we decided to use the optical encoder for our implementation. Its ability to maintain consistent data quality makes it the most suitable choice for our project's requirements.

The following step was to mount the sensors on the machine. Encoders were mounted on each of the axis of the machine as can be seen in figure.

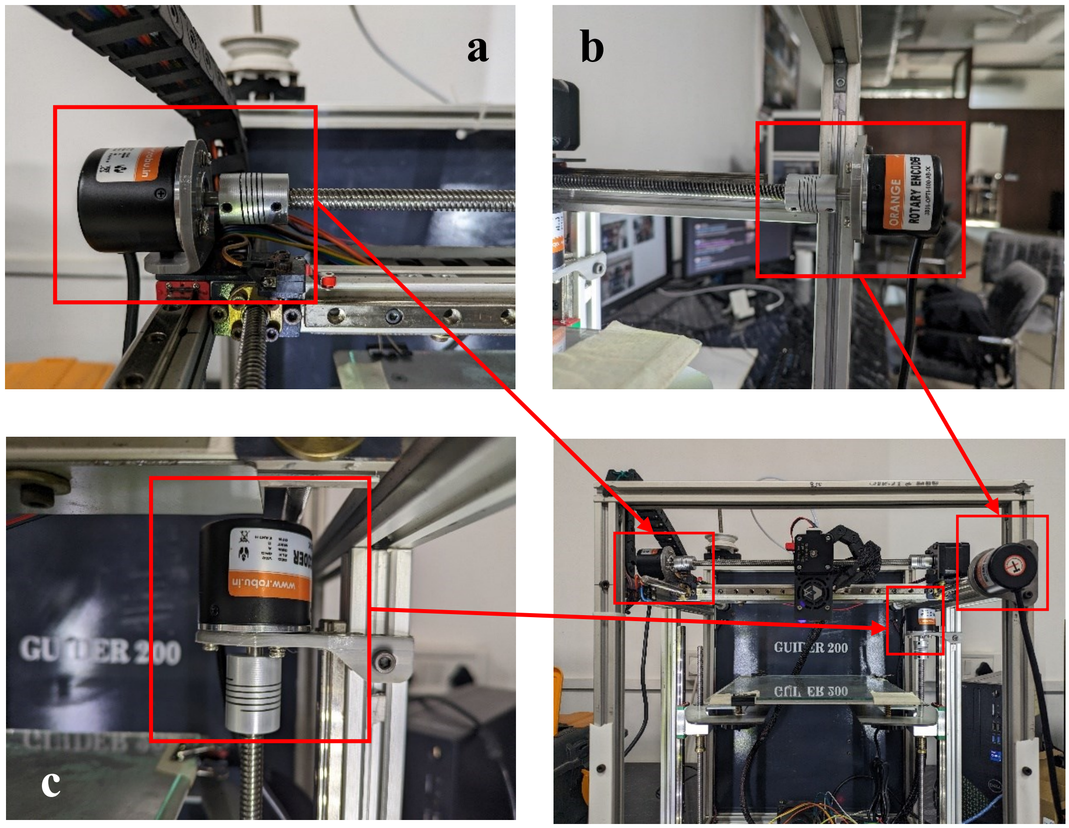
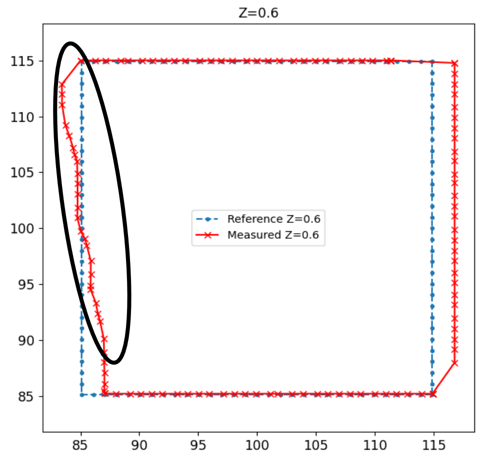


Figure 9 Implementation of Optical Encoder on FDM machine

To evaluate the system's efficacy in error detection, deliberate deviations were introduced during material deposition. This methodical approach enabled a comprehensive assessment of the system's capability to identify anomalies. The ensuing section delineates the findings from these deliberate error tests, elucidating the system's proficiency in discerning and flagging intentional deviations from the normative printing process.

In each of the diagram we can clearly see that the errors in the deposition process are being detected by the Data Collection System in real time from the FDM machine


Z=0.6
Reference Z=0.6
Measured Z=0.6
115
110
105
100
95
90
85
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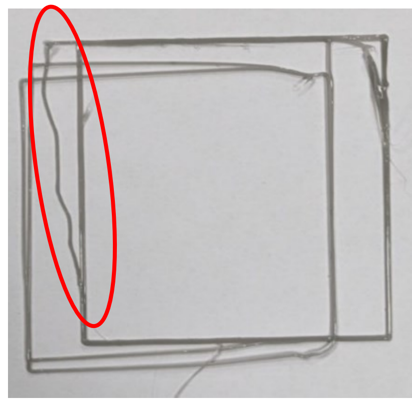
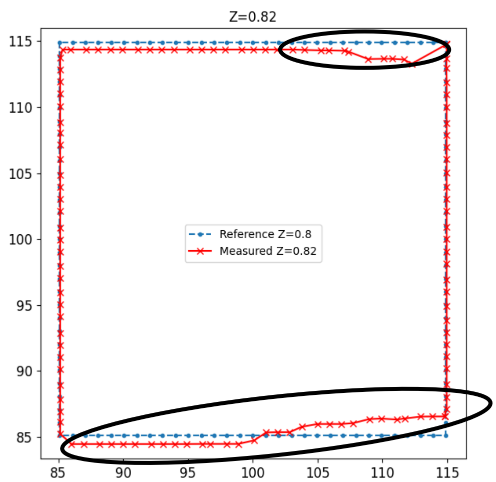
115




Z=0.82
Reference Z=0.8
Measured Z=0.82
115
110
105
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95
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85
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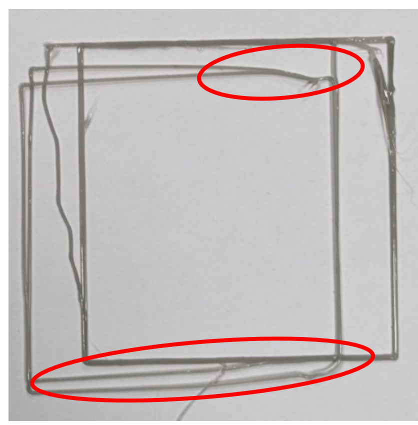
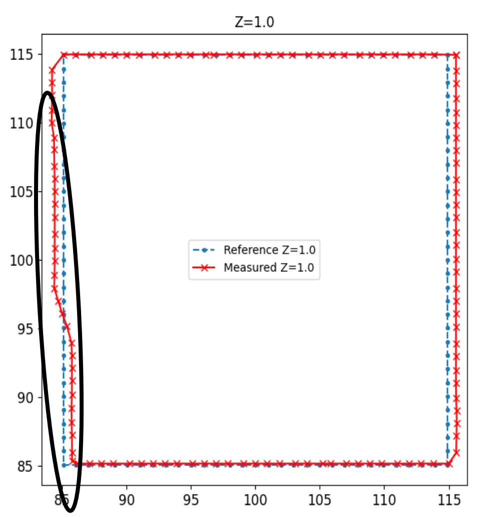
115




Z=1.0
Reference Z=1.0
Measured Z=1.0
115
110
105
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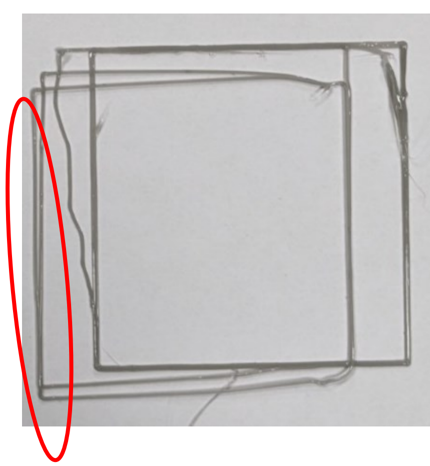
115



For the next analysis DCS was tested with the actual part and its detection. For that we made a CAD model of a Spanner as a test case. The layer height for

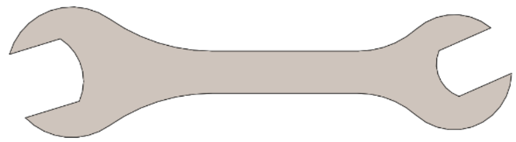
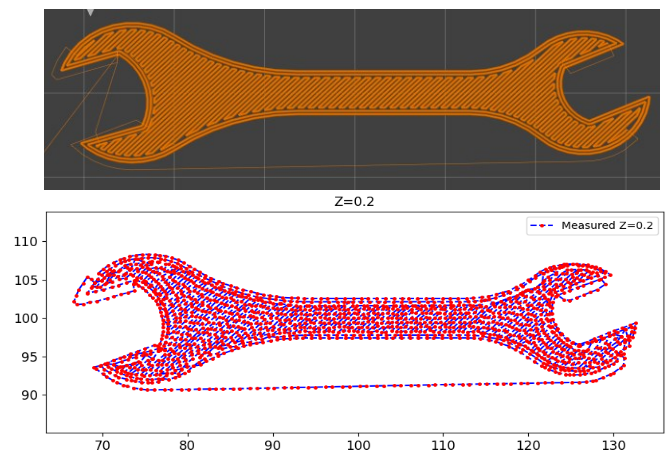


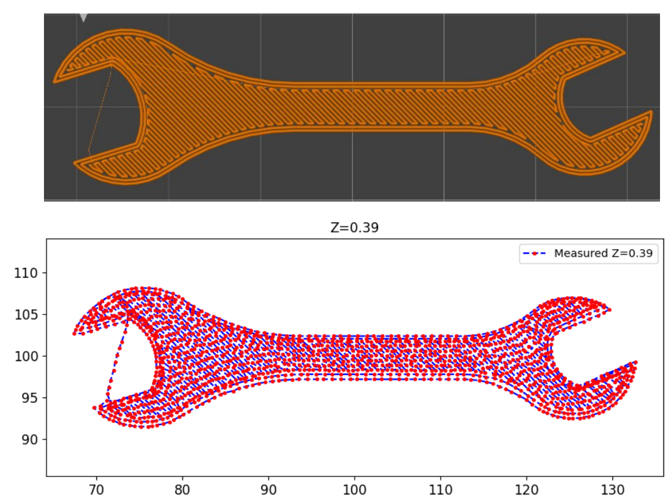
Figure 10 Spanner CAD design

this process was set at 0.2mm and the thickness of the part was 1mm for testing. The 5 layers and their collected data can be seen in the figures. The orange images are the sliced sections at each of the layer number and the actual motion of the nozzle head that is being read by the DCS in the image below that. So,

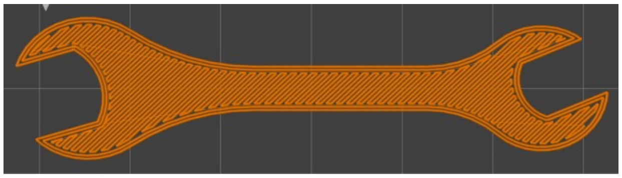
Layer 1



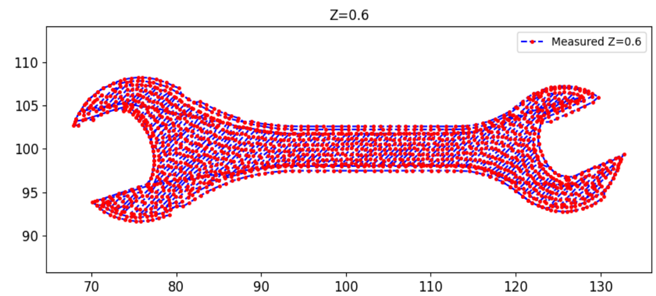
Layer 2

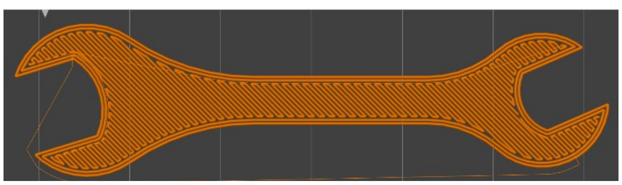


it can be concluded that the approach for the monitoring of the nozzle head during the production process is working fine.

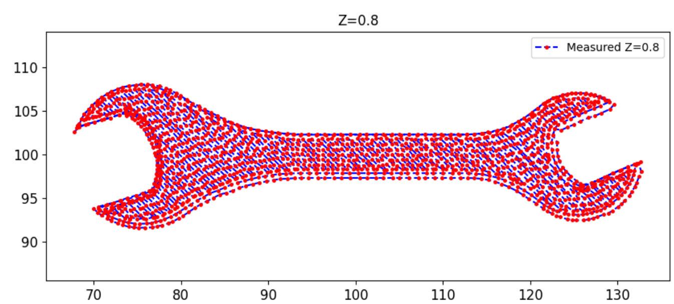


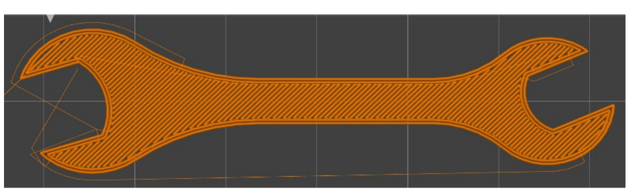
Layer 3



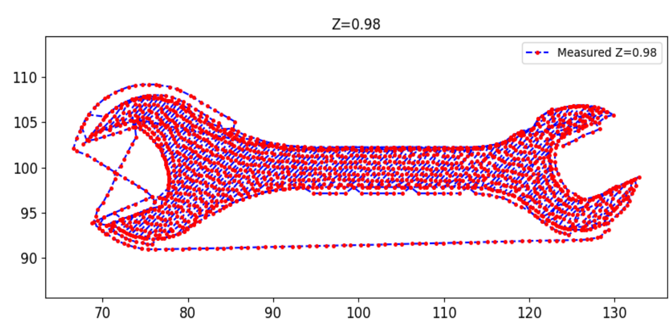


Layer 4





Layer 5



To check the replicability, we decided to do the same setup on another FDM machine as well. The machine used for this setup is Creality's Ender 3 Neo. It is a 3D printer known for its affordability and reliability. It's popular among hobbyists and enthusiasts for its ease of use and versatility. With a sturdy frame and user-friendly interface, the Ender 3 Neo allows users to create high-quality prints with precision. Its open-source nature also enables users to customize

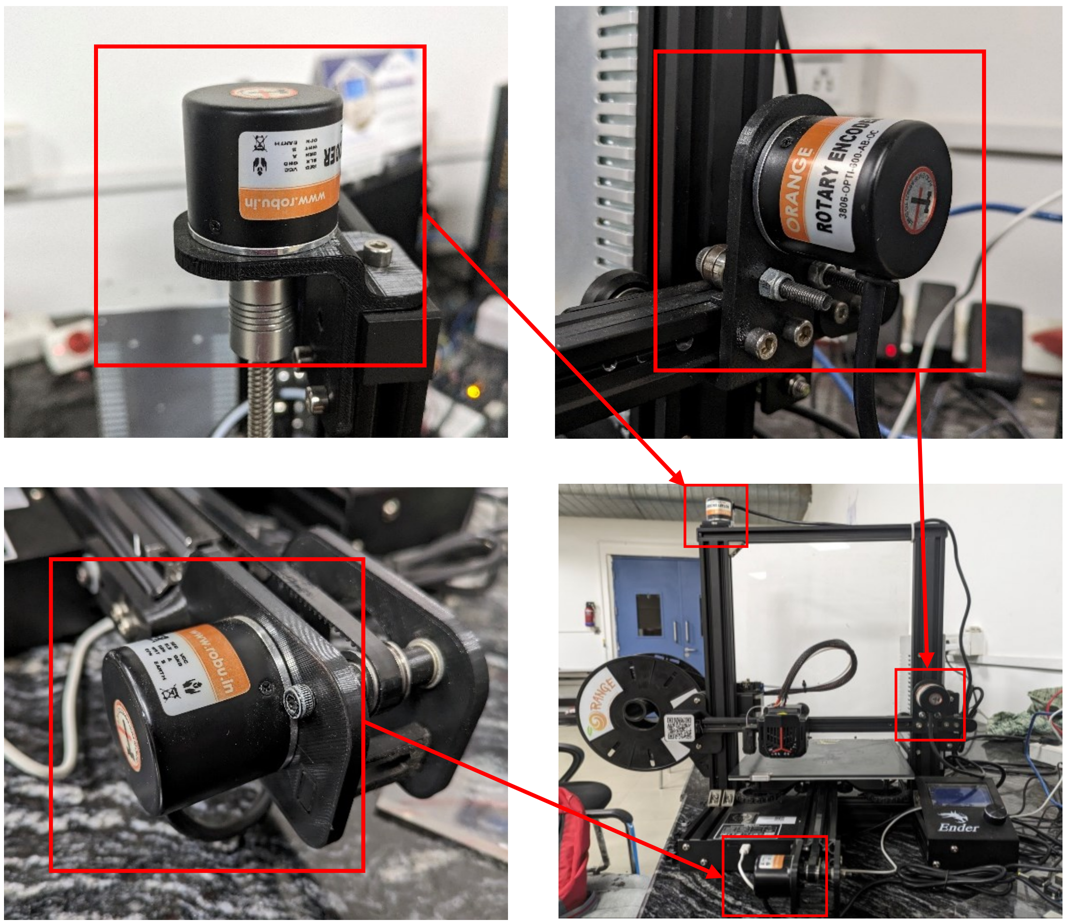


Figure 11 Implementation of Optical Encoder on FDM machine

and upgrade the printer according to user's needs. The X and Y axis of the machine are belt driven and the Z axis is driven by lead screw. So accordingly, sensors were mounted on the machine in order to monitor the axes.

These 3 optical rotary encoders are connected to an individual Arduino which powers each of the sensor and collects the data from them and sends to a main Arduino board. The communication protocol used for the development of this

DCS is IIC or I2C (Inter Integrated Circuits). The I2C is a widely used communication protocol designed for short-distance communication within electronic circuits. Developed by Philips in the 1980s, I2C enables efficient communication between microcontrollers and peripheral devices such as sensors, displays, and memory modules. The protocol uses a simple, two-wire interface consisting of a Serial Data Line (SDA) and a Serial Clock Line (SCL). These lines are used for bidirectional data transfer, where multiple devices can be connected to the same bus, each with a unique address. The master device initiates communication by generating a clock signal and sending address information, while the slave devices respond according to

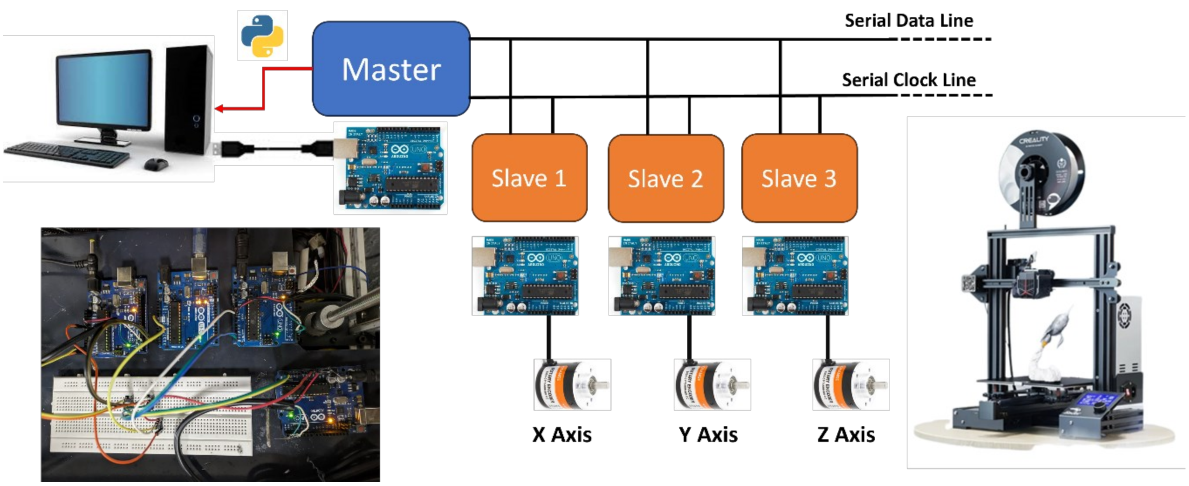


Figure 12 Communication in DCS

their assigned addresses. One of the key advantages of the I2C protocol is its simplicity and flexibility, which make it ideal for embedded systems and applications where pin count and wiring complexity need to be minimized. I2C supports multiple masters and slaves on the same bus, facilitating complex communication patterns in a straightforward manner. The protocol's standard speed modes range from 100 kHz (Standard-mode) to 3.4 MHz (High-speed mode), catering to various performance requirements. Despite its relatively low data rates compared to other protocols, I2C's ease of implementation and low resource requirements make it a popular choice for inter-device communication in consumer electronics, industrial automation, and various other fields. Here, the slave sensors are the optical rotary encoders connected to each axis of the FDM machine and they are sending the data to the main master which is combining the data from all the 3 slaves and giving the data in real time.

A user-friendly HMI for the Data Collection system was developed with Tkinter in python for easy usage and collecting of the data during the manufacturing process. The HMI has two primary functionalities. The first functionality is to create a folder where the data related to the product will be stored throughout the manufacturing process. This ensures that all relevant information is organized and easily accessible for analysis and record-keeping. The second functionality involves establishing a connection with the Data

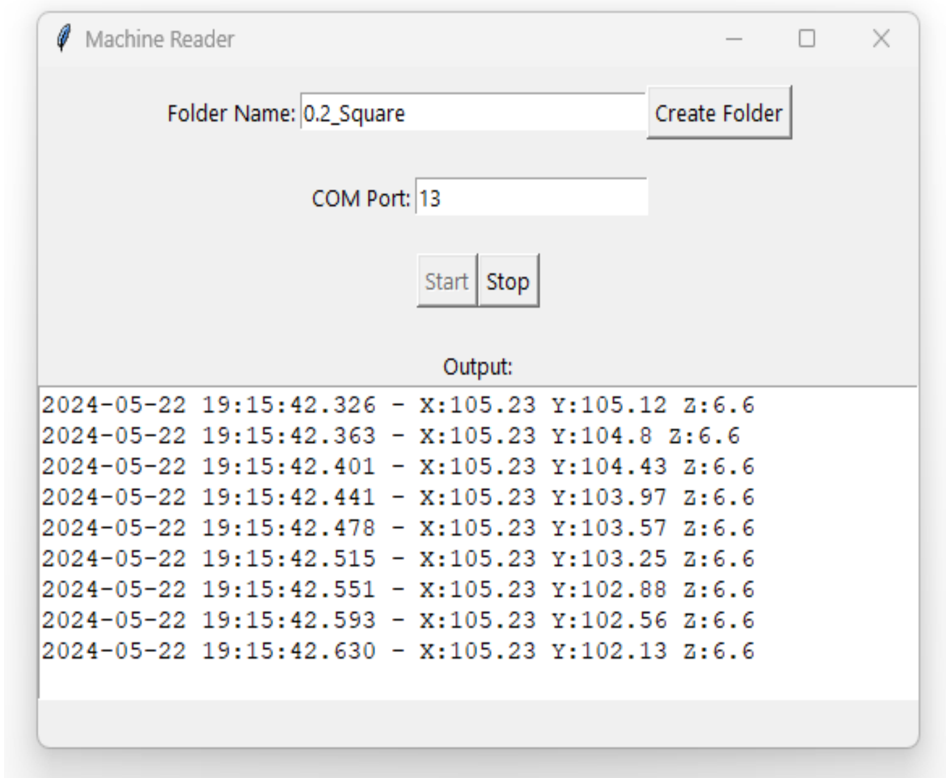


Figure 13 User Interface for Data Collection System

Collection system (DCS) via a USB serial connection. This connection enables seamless communication between the manufacturing equipment and the control system, facilitating efficient data exchange and system monitoring.

Additionally, the output window of the system provides real-time feedback on the position of the nozzle head. This feature is crucial for monitoring and ensuring the precision of the manufacturing process, as it allows operators to observe and adjust the nozzle head's position as needed during production.

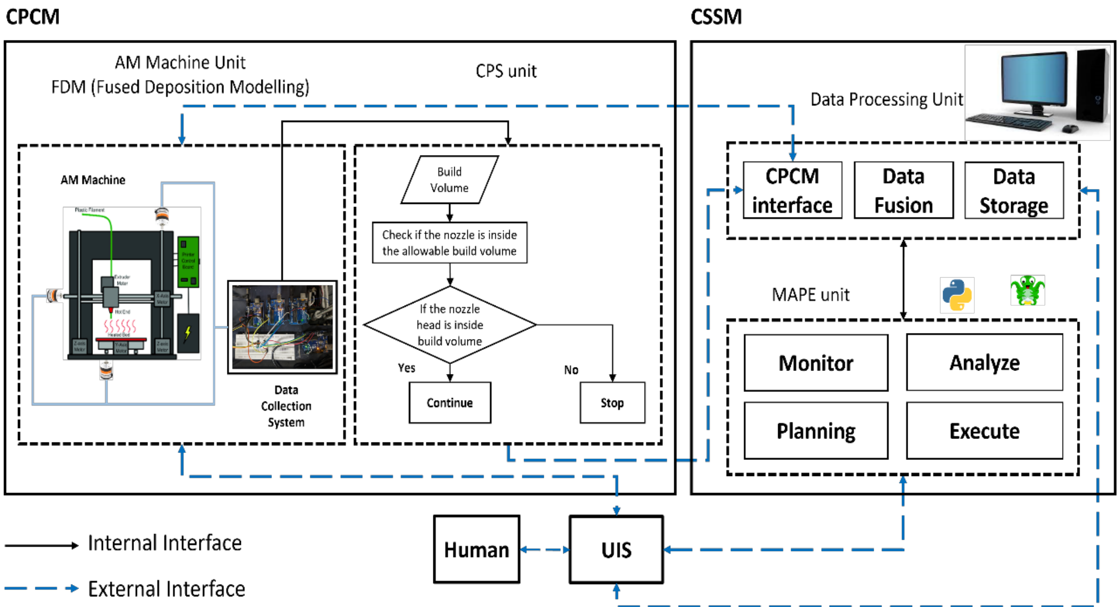


Figure 14 Architecture of developed system

In this way the algorithm for the analysis is standardized with the ISO standard. In this way the developed data collection system and the analysis algorithm can be used to analyse the FDM process. Finally, the developed system is standardized as ISO23704, and the architecture developed for this is system can be seen as **Figure 14**

Chapter 5 Experiments, Results & Discussion

In this chapter, we will see the results and findings obtained from this research. This will involve utilizing appropriate data visualization techniques to analyse and interpret the results in relation to the research objectives.

Table 2 Machine Parameters

Feed Rate (mm/sec)	
X	500
Y	500
Z	5
Acceleration (mm/sec^2)	
X	500
Y	500
Z	500
Print Settings (mm/sec^2)	
Print Acceleration	500
Retraction Acceleration	500
Travel Acceleration	1000

The process parameters for the FDM machine are stated in the table above. The machine was tested for variations in machine parameters by adjusting the Feed Factor. The Feed Factor changes all the machine parameters proportionally. For example, when the Feed Factor was set to 100%, the machine parameters were as shown in the table above. When the Feed Factor was reduced to 75%, all parameters adjusted to 75% of their original values, and similarly for 50%. This experiment was conducted with three different Feed Factors. Additionally, to account for all variability, the layer size was varied in three steps: 0.1mm, 0.2mm, and 0.3mm for the same part design. Also, as the FDM machine has a belt driven system for X and Y axis, there can be a chance of the belt tension getting loose with time which will eventually degrade the quality of the product. So, the variation in the belt tension was also taken into consideration for this study. Tension 1 being highest, 2 moderate and 3 being the lowest belt tension. This allowed us to see how changes in Feed Factor, layer size and Belt tension affect the machine's performance and accuracy in the product. For testing the data collection system, a Square Shell was used as a standard design for all types of tests. The analysis involves two main steps. First, we develop a baseline error plot. Second, we calculate the error from the process in real time. In this study, we examined three different combinations of the Square Shell. These combinations used layer heights of 0.1mm, 0.2mm, and 0.3mm. Each Square Shell was sliced with these different layer heights for the purpose of slicing and developing the part. This approach helps us understand how different layer heights affect the accuracy and errors in the data collection process.

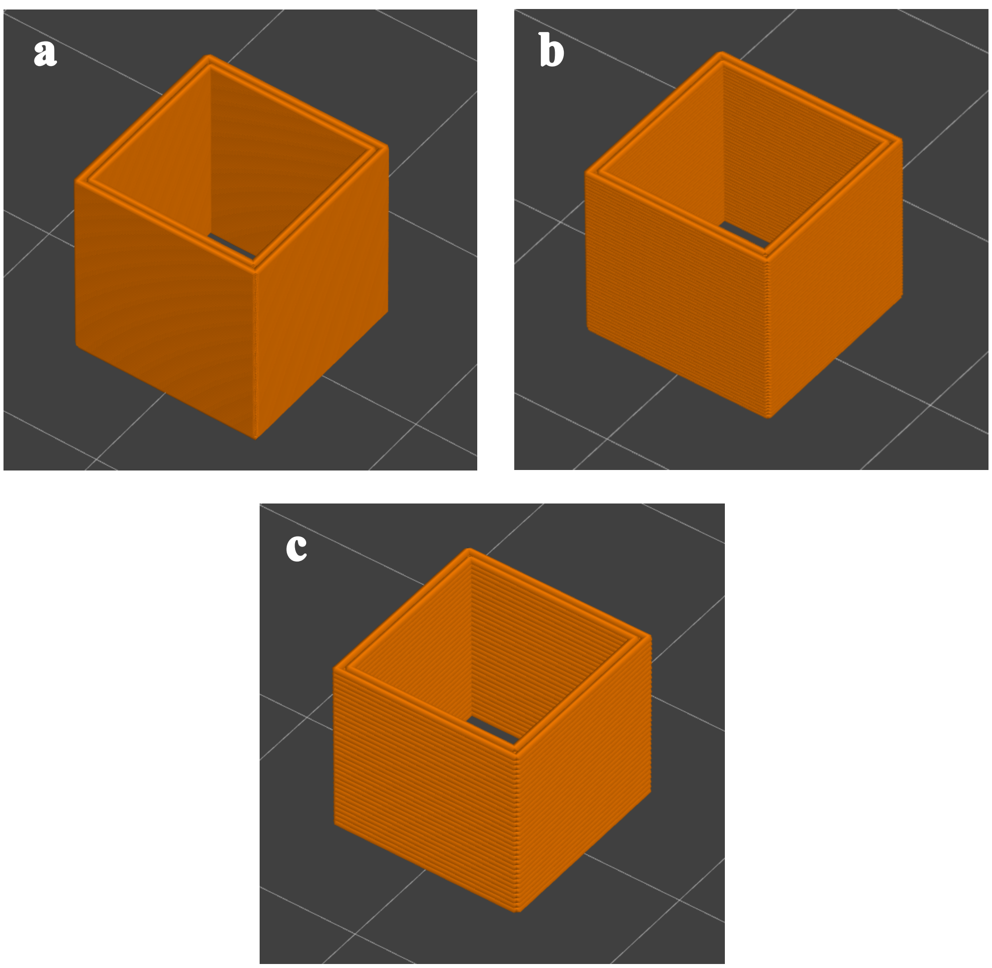


Figure 15 Square Shell a) 0.1mm b)0.2mm 3)0.3mm

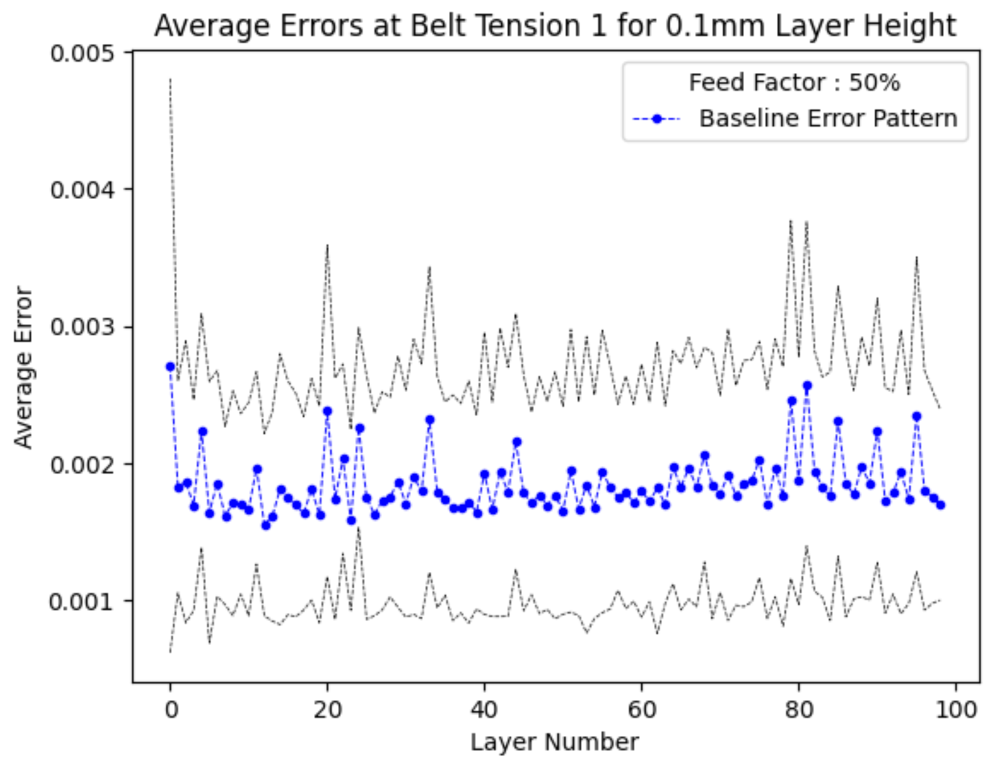


Figure 16 Baseline Error Pattern of Square Shell 0.1mm at 50% Feed Factor

Figure 16 is the baseline error plot for the Square Shell with 0.1mm layer height at 50% feed rate and at the highest tension. Here we can see that the average error is in the same region and the pattern line is more or less straight line due to prismatic nature of the Component. The black dashed lines above and below the baseline error plot are the standard deviations of the average error for each of the layer. This will act as a reference pattern for the parts that will be newly produced with the same machining parameters. For the first layer the error value is being the highest as for better adhesion the first layer was kept very close to the nozzle head. Note that the error values are increasing as the feed factor is increasing, signifying the increase in the dimensional error as the speed is increasing.

Similarly, the baseline error plots can be observed for the layer height of 0.2mm and 0.3mm for the Square Shell with different feed factor levels from **Figure 17** to **Figure 24**

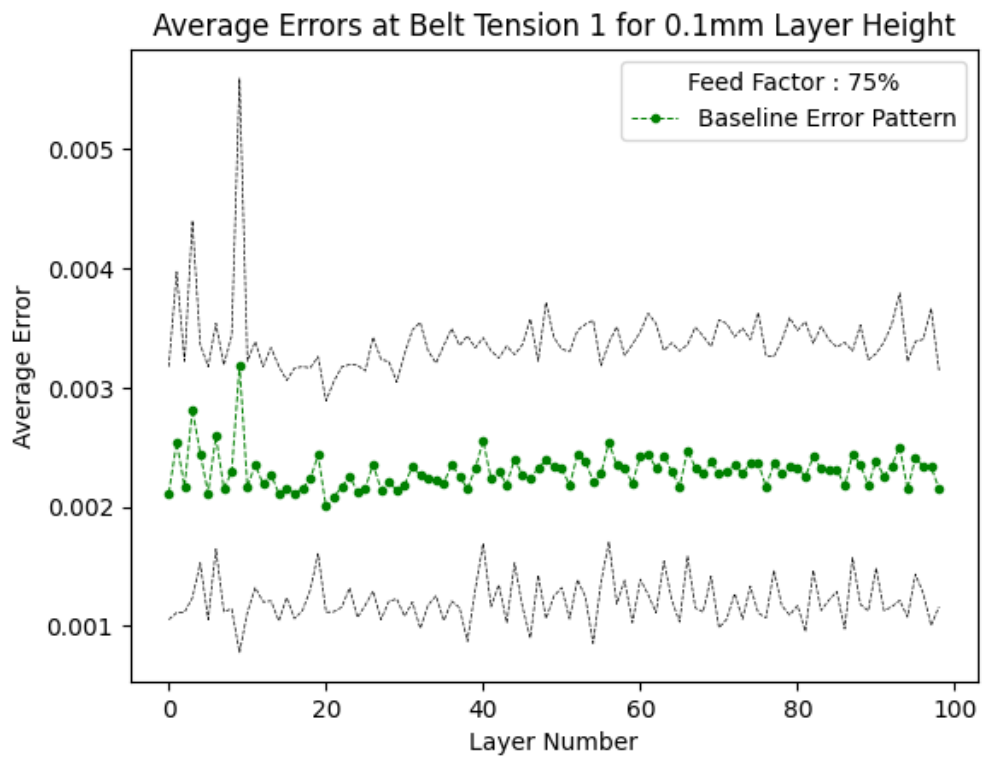


Figure 17 Baseline Error Pattern of Square Shell 0.1mm layer height at 75% Feed Factor

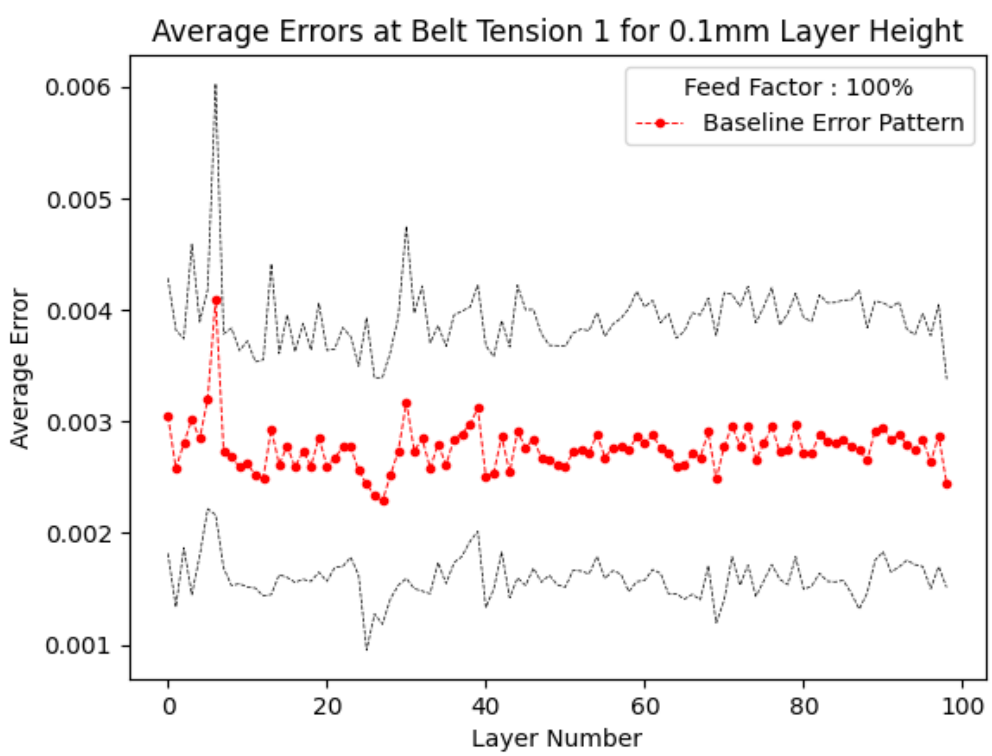


Figure 18 Baseline Error Pattern of Square Shell 0.1 mm layer height at 100% Feed Factor

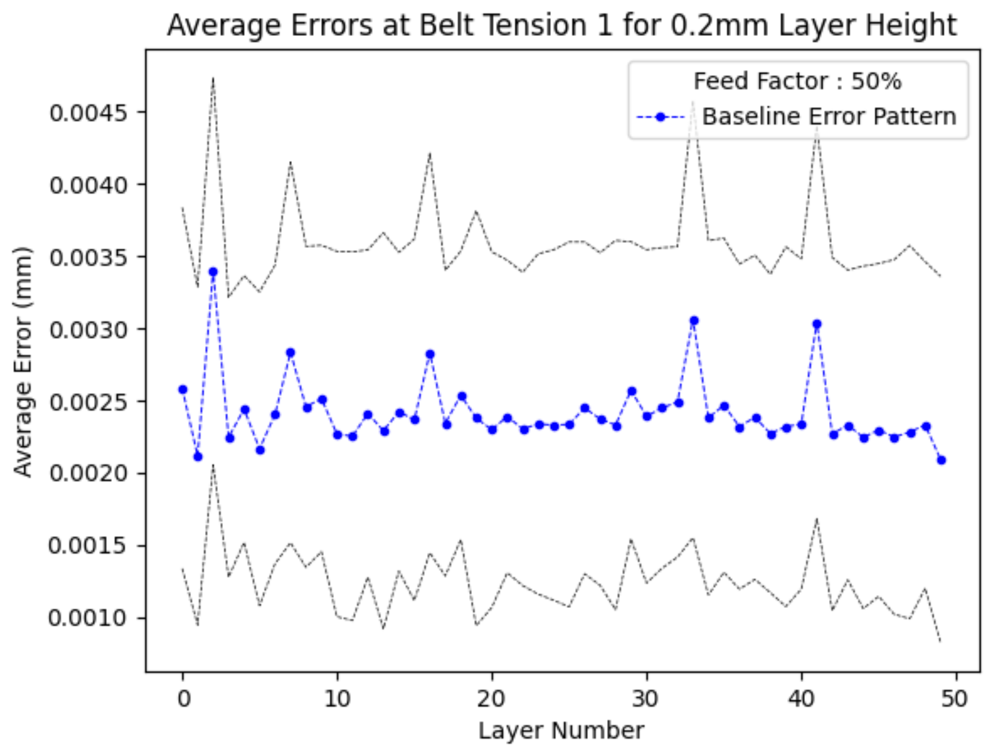


Figure 19 Baseline Error Pattern of Square Shell 0.2mm layer height at 50% Feed Factor

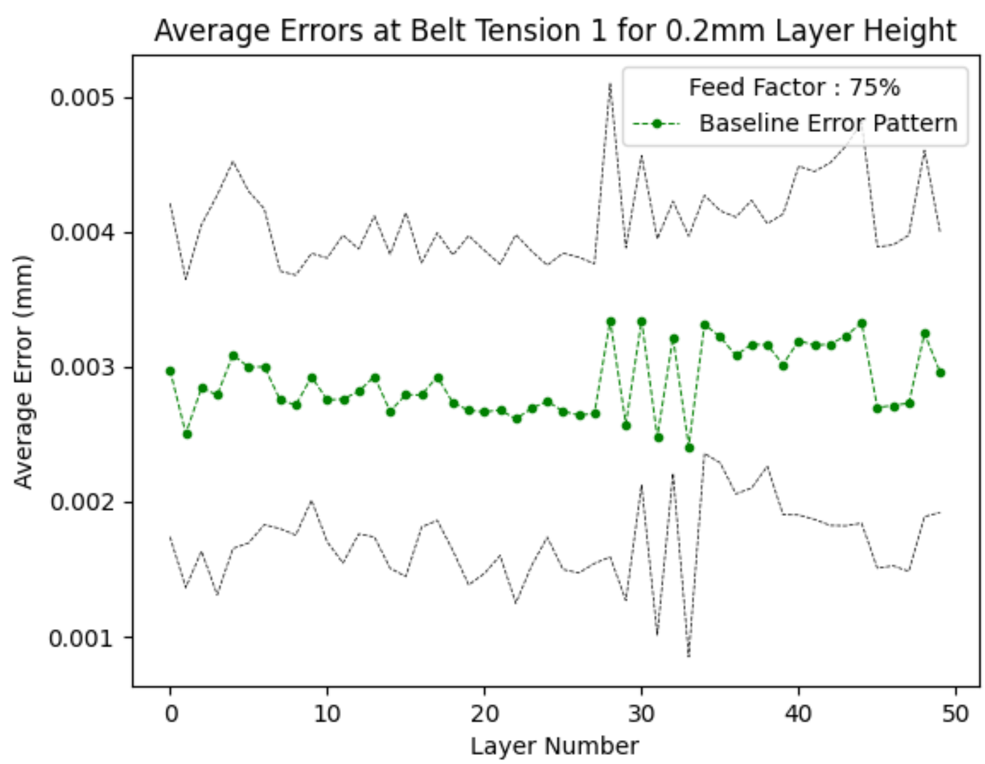


Figure 20 Baseline Error Pattern of Square Shell 0.2mm layer height at 75% Feed Factor

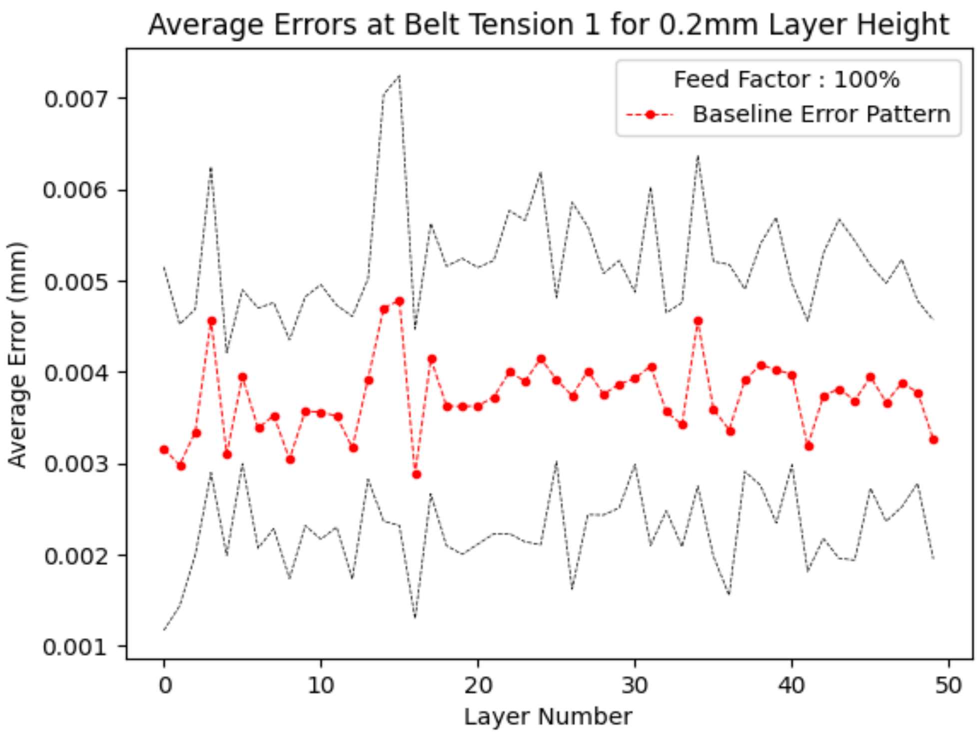


Figure 21 Baseline Error Pattern of Square Shell 0.2mm layer height at 100% Feed Factor

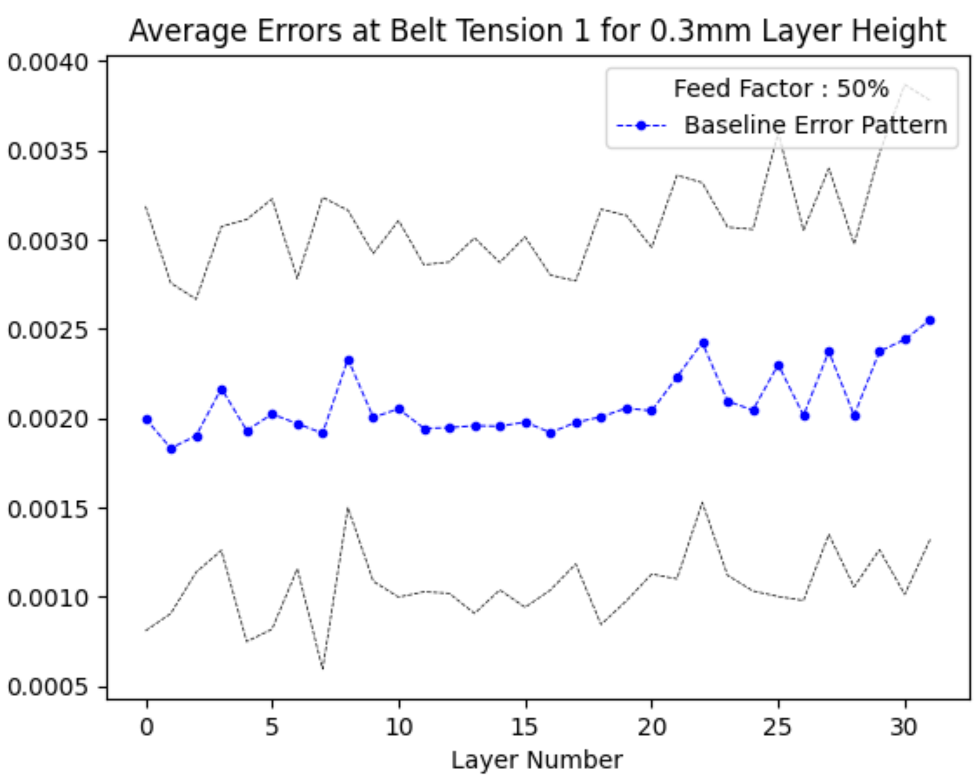


Figure 22 Baseline Error Pattern of Square Shell 0.3mm layer height at 50% Feed Factor

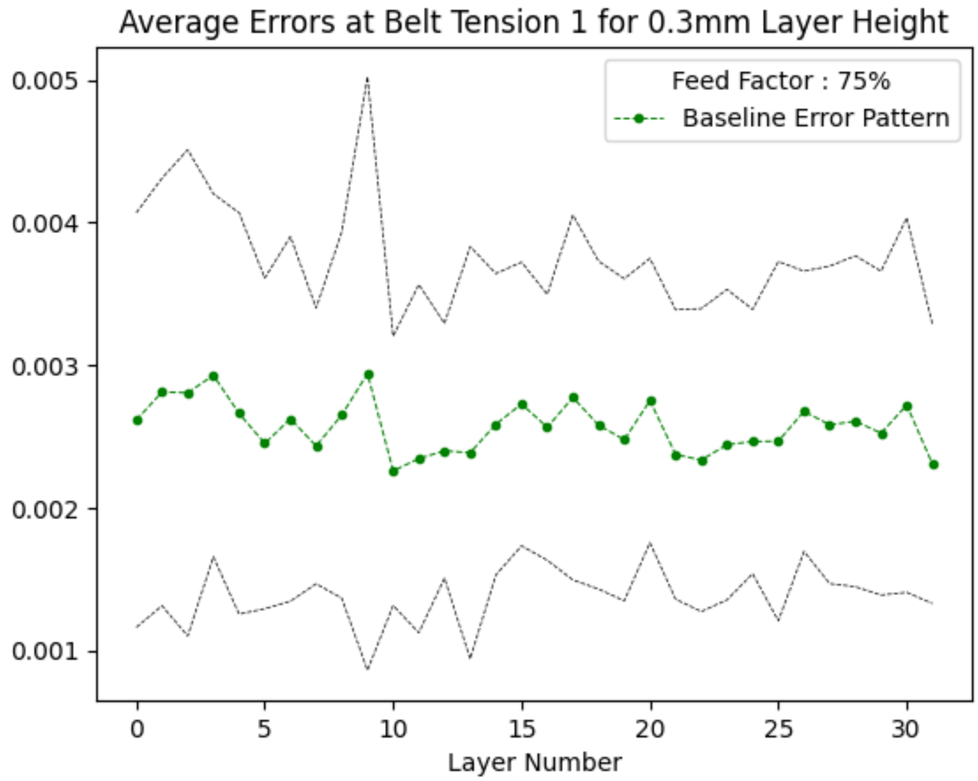


Figure 23 Baseline Error Pattern of Square Shell 0.3mm layer height at 75% Feed Factor

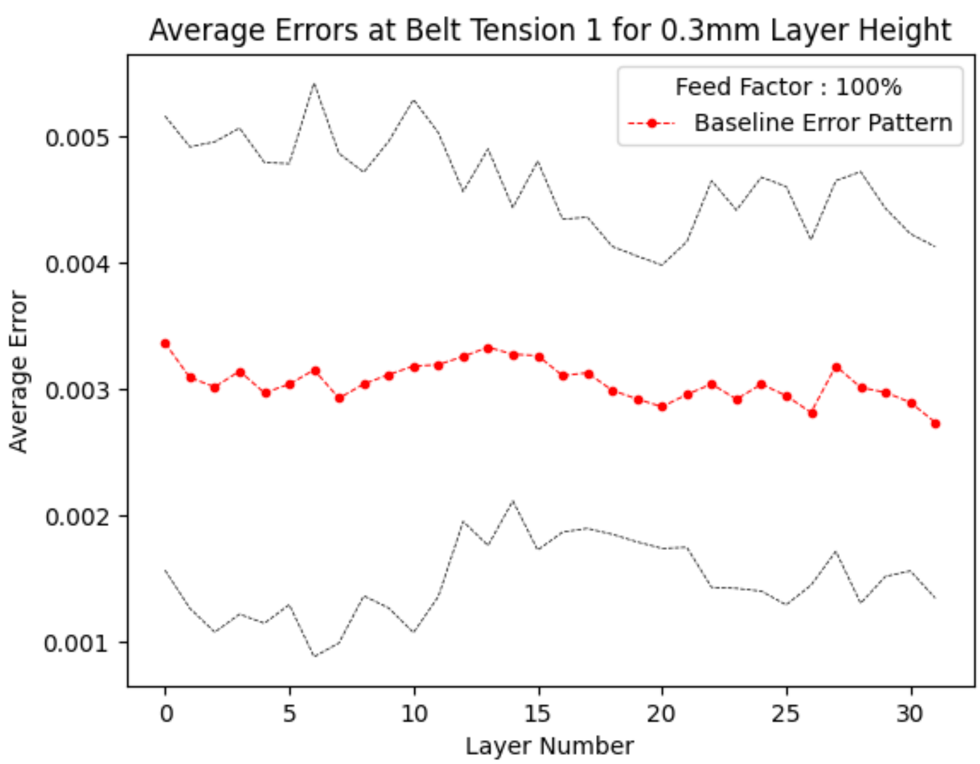


Figure 24 Baseline Error Pattern of Square Shell 0.3mm layer height at 100% Feed Factor

It is evident that the variation in these different factors has influenced the value of the average error. However, the overall pattern remains nearly the same as a straight line, primarily due to the shape of the component. By using this baseline error plot as a standard, we can monitor the manufacturing process quality in real time. This approach allows us to detect deviations from the expected error pattern early, so we can intervene quickly to maintain product quality and consistency. For example, if we notice that the error value starts to deviate from the baseline plot, we can immediately check the factors that might be causing this deviation and make necessary adjustments to bring the process back on track. Thus, the baseline error plot is a crucial tool for ensuring that the manufacturing process stays within acceptable quality limits. It helps us identify and correct issues before they become significant problems, ensuring that each component produced meets the required quality standards. This supports the production of reliable and high-quality components, which is essential for maintaining customer satisfaction and trust in our manufacturing processes.

To evaluate the error detection capability of the developed data collection system, we conducted a simulation by intentionally inducing errors during the manufacturing process of a Square Shell test subject. The test subject was manufactured with a specified layer height of 0.2mm. To create controlled errors, we manipulated the belt tension of the X-axis of the machine across three distinct stages. Additionally, we varied the feed factors in three corresponding stages. This approach allowed us to observe and analyse how effectively the system could detect errors introduced by these modifications. The test parameters for this experiment are as **Table 3**,

Table 3 Testing Parameters for 0.2mm Square Shell

Feed Factor (%)	50, 75, 100
Belt Tension Level	1, 2, 3
Layer Height (mm)	0.2

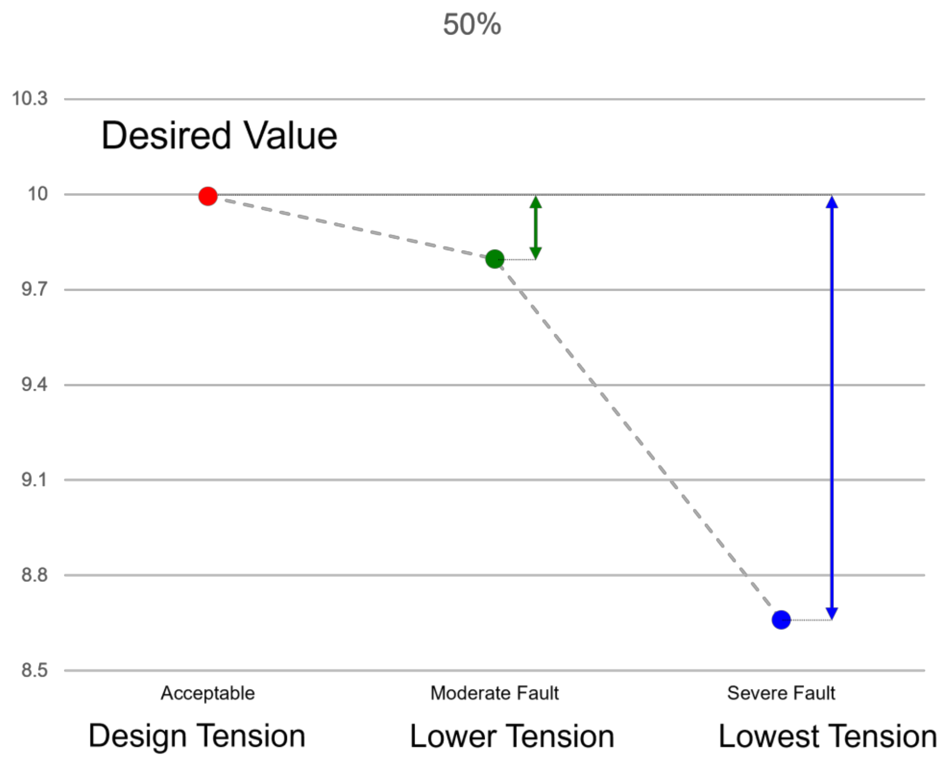


Figure 25 Variation in process error due to belt tension variation at 50% Feed Factor

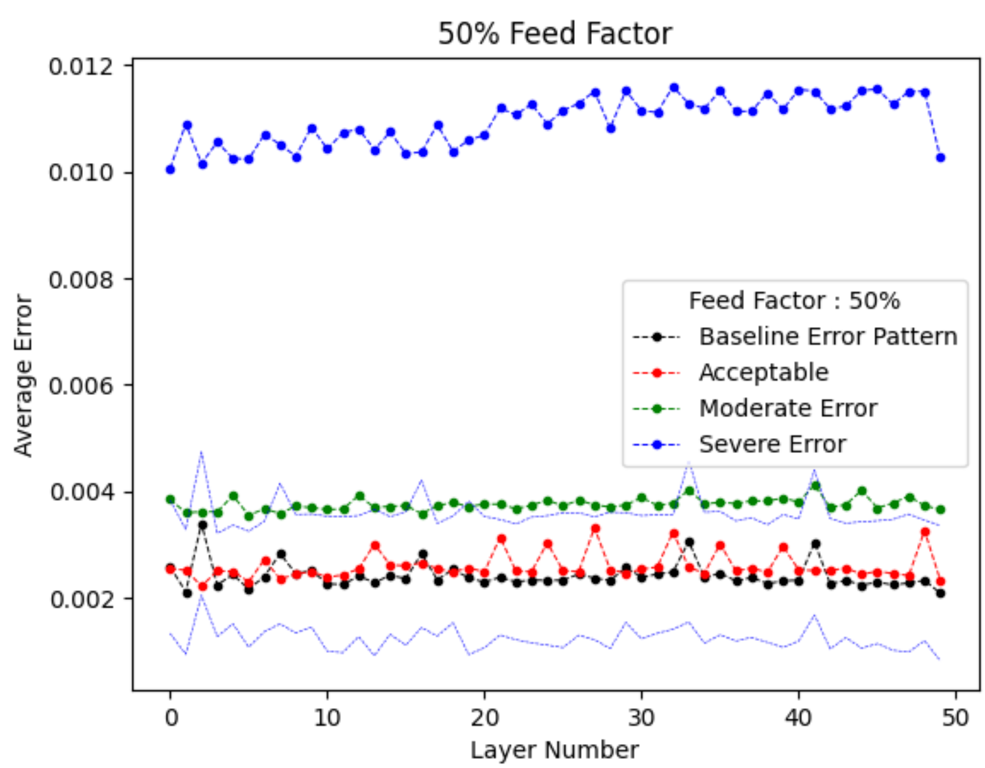


Figure 26 Error Pattern comparison for different tension level at 50% Feed Factor

Figure 25 and **Figure 26** are the results for this different experiment. When the product is manufactured with the required design tension the error during the manufacturing process lies within the acceptable range, also the dimension of the final product is also in the acceptable range as can be seen in the red error pattern in the **Figure 26**..

But when the belt tension is reduced, the tool head's movement becomes inaccurate because the lower tension prevents the belt from gripping the pulley properly. This improper motion results in the final component being smaller than intended, introducing errors into the finished product. The data collected by the DCS clearly reflects this increase in error as the green error pattern in figure. As the belt tension decreases, the grip on the pulley weakens, leading to a reduction in the component's dimensions. This generation of error is captured by the DCS and is evident in the collected data, demonstrating how changes in belt tension directly impact the precision of the manufacturing process.

As the belt tension is lowered further, severe faults are induced in the process, and the dimensions are further reduced by a significant level. This reduction introduces more severe errors. The severity of these faults and the corresponding decrease in component size can be clearly seen in the DCS data plots. The impact of reduced belt tension is significant and becomes progressively more pronounced as the tension decreases. Furthermore, this trend is consistent across different feed factor levels. Regardless of the feed rate, the reduction in belt tension consistently leads to improper pulley grip, resulting in smaller component dimensions and increased error rates.

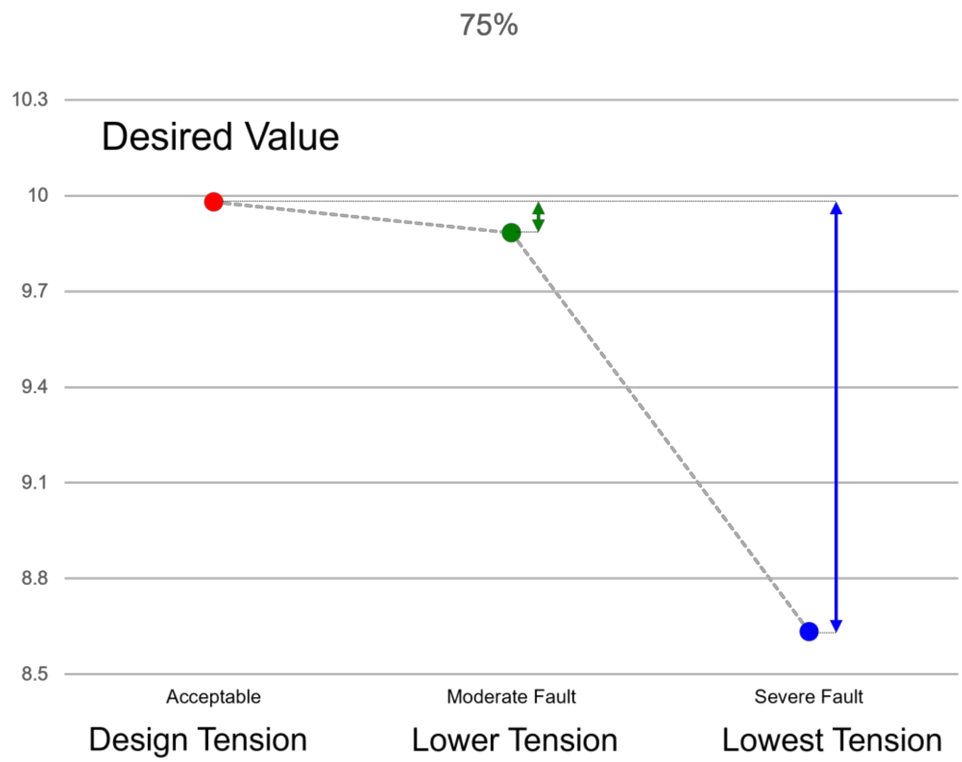


Figure 27 Variation in process error due to belt tension variation at 75% Feed Factor

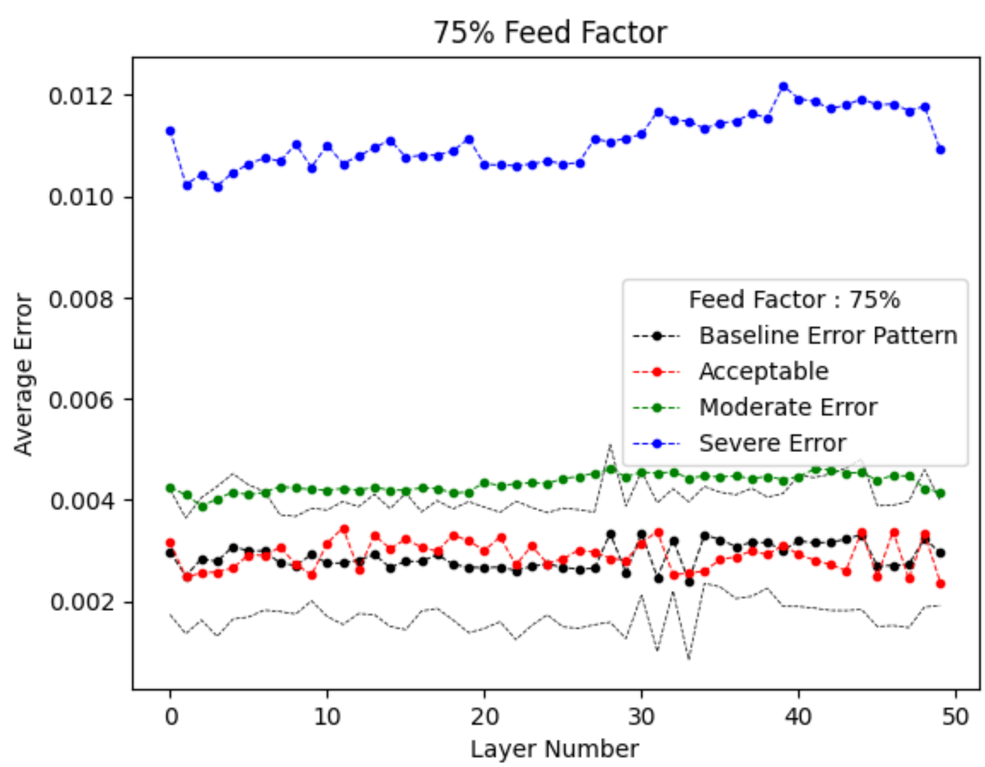


Figure 28 Error Pattern comparison for different tension level at 75% Feed Factor

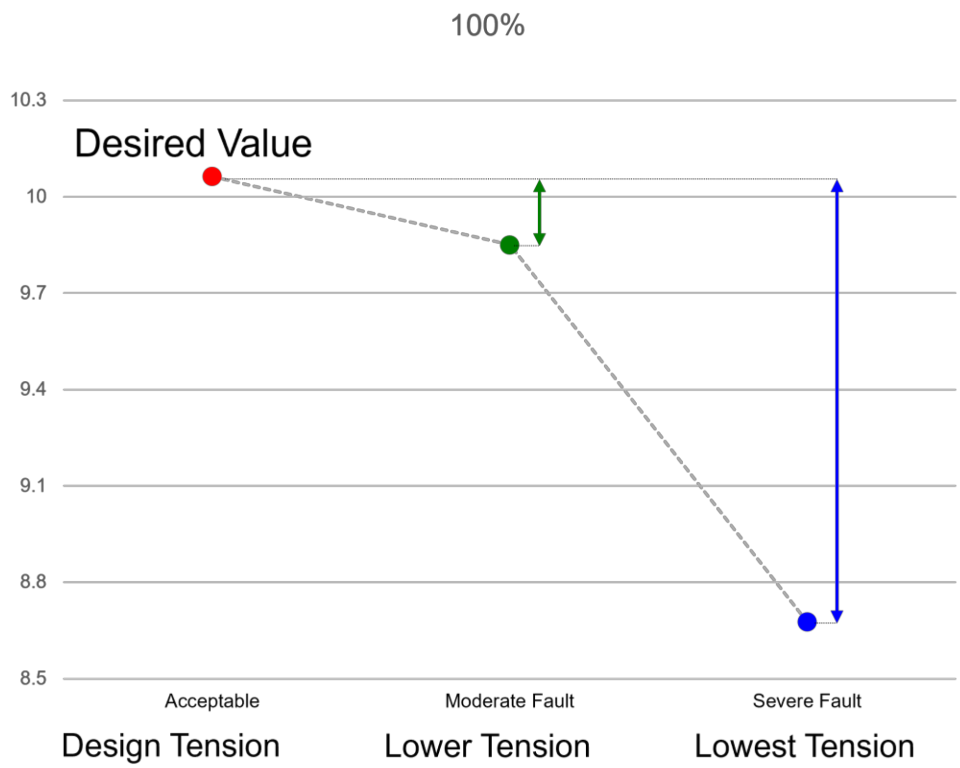


Figure 29 Variation in process error due to belt tension variation at 100% Feed Factor

Figure 30 Error Pattern comparison for different tension level at 100% Feed Factor

After carefully reviewing the plots from our data collection system, it's clear that changes in belt tension lead to detectable variations in error across different manufacturing speeds. Our analysis shows that our system reliably identifies and tracks these variations, demonstrating its effectiveness in maintaining accuracy and consistency in various operational scenarios.

To expand the scope of our evaluation of the Data Collection System, we opted to manufacture additional components featuring varied and intricate shapes. Our first selection was a Spur Gear. Throughout this experimental phase, we maintained a consistent layer height of 0.2mm to ensure uniformity. Below, the CAD design of the gear is presented, providing a visual representation of its structure.

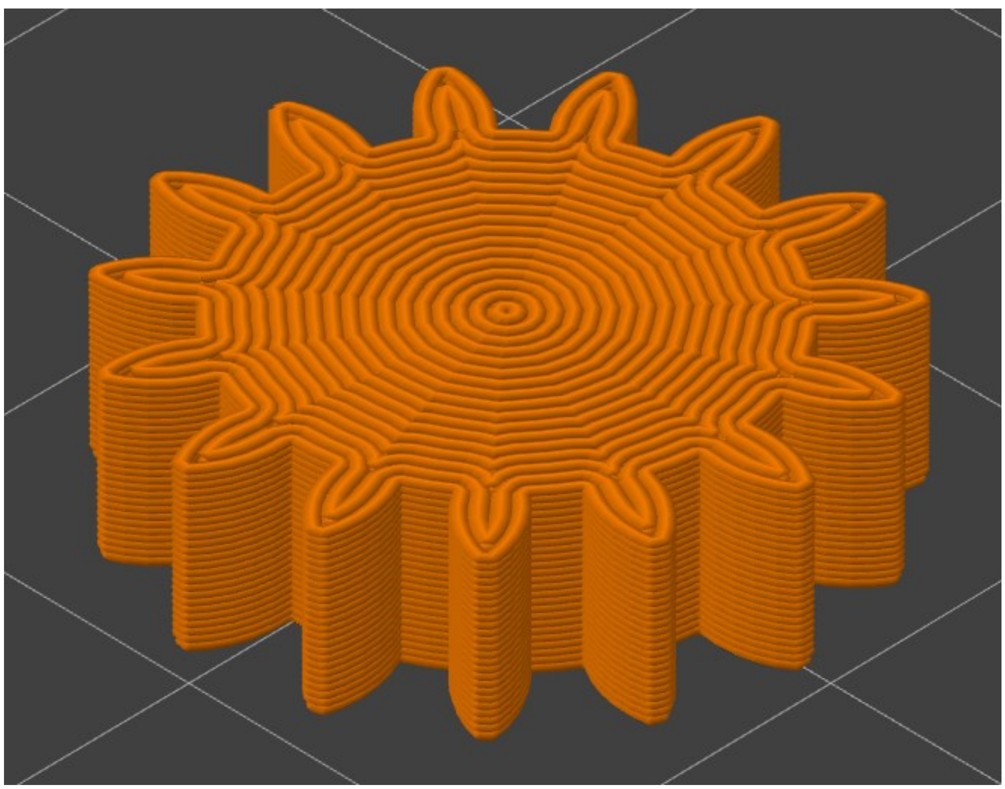


Figure 31 CAD design for Spur Gear

The Spur gear was also printed with different Feed Factors from 50% to 100% in order to consider the variability that might arise in product due to speed variation and the results are as below

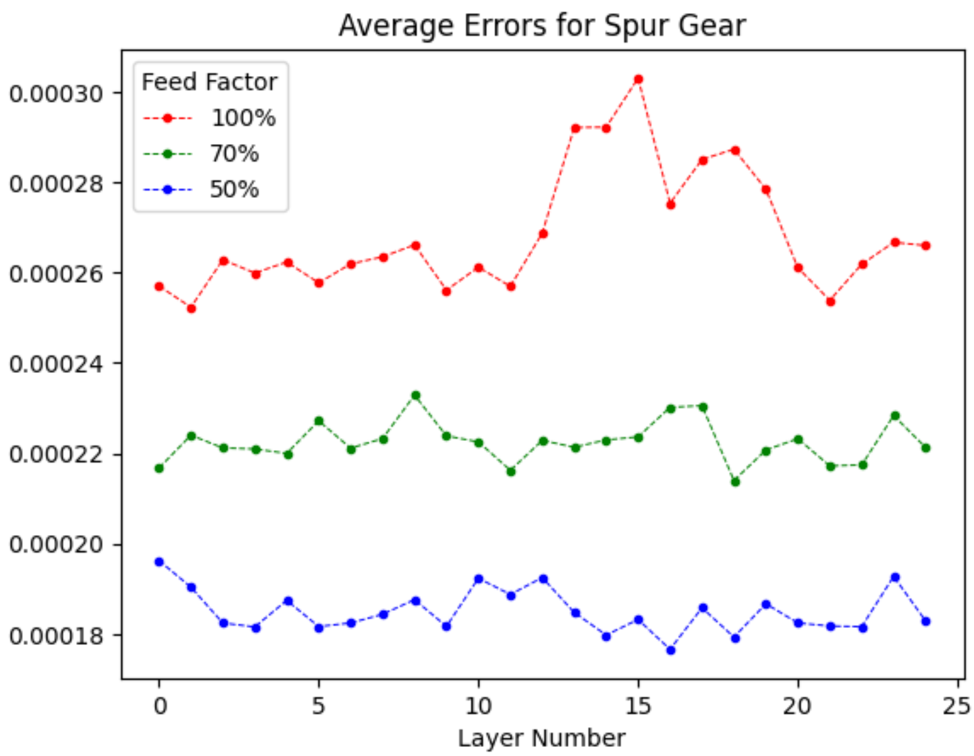


Figure 32 Baseline Error plot for Spur Gear at different Feed Factor

So, it is clearly visible from **Figure 32** that the nature of the Baseline error pattern is straight line nature. It depends on the structure of the component being manufactured. Here the gear is of prismatic nature so the baseline error pattern for each feed factor is a straight line. As the Feed Factor is increased, the printing speed increases also acceleration is increased, which eventually decreasing the accuracy of the movement of the nozzle tool head. Thus, the error can be seen increasing with the increasing Feed Factor in **Figure 32** plot. In this way the analysis of the spur gear at different speeds was done.

The next part of our consideration of the analysis is a Propeller. The design as follows. Propeller was also manufactured with different feed factors in order to consider for any variability that arise in the component due to change in the speed and accelerations

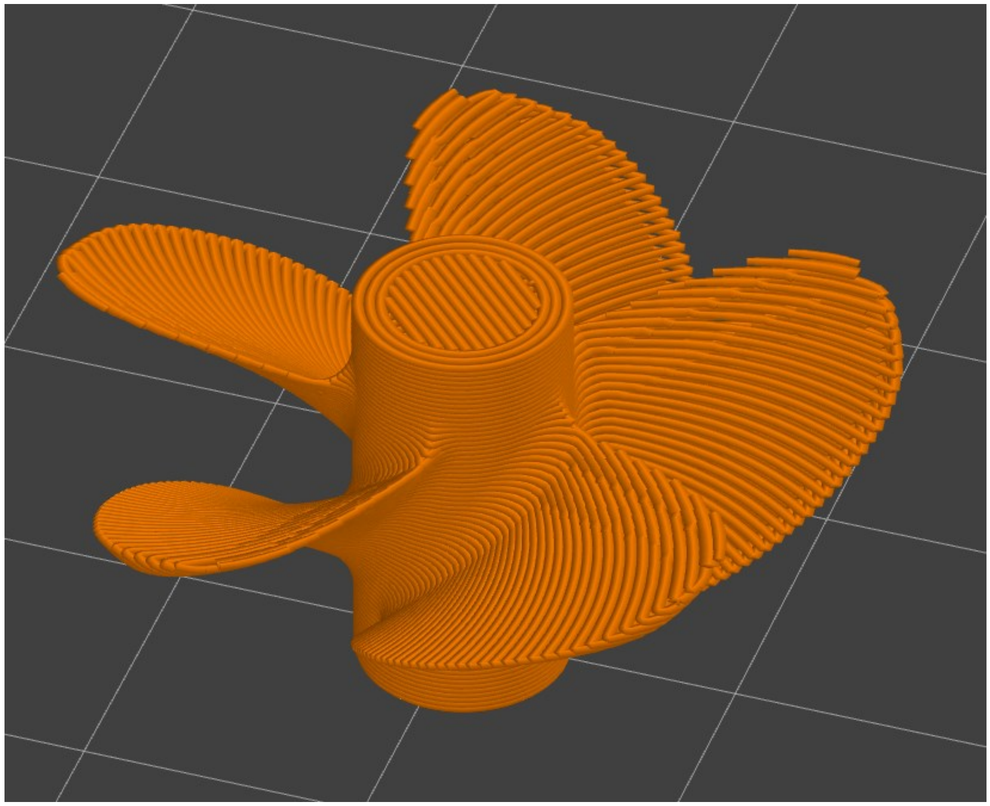


Figure 33 CAD design for Propeller

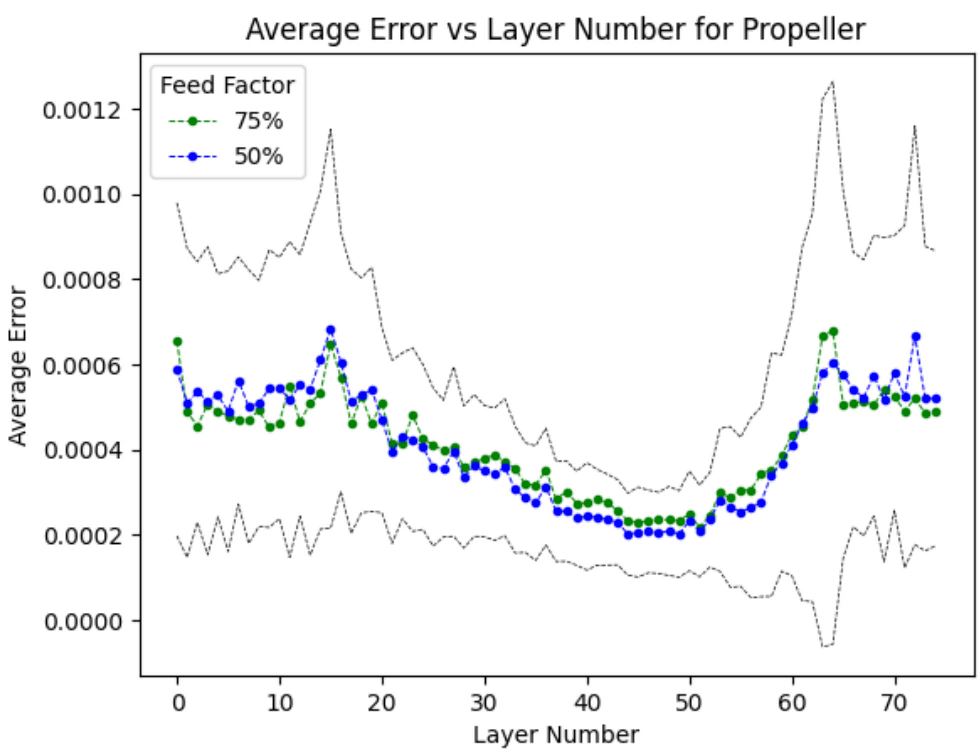


Figure 34 Error Pattern for Propeller at different Feed Factors

As the shape of the component is not prismatic, the baseline error plot will also have structure other than the straight line which will be dependent on the number of points in each layer of the reference data. As more points the error will be distributed over more points. With the developed DCS we can also reverse engineer the final product that has been manufactured as can be seen in the **Figure 35**

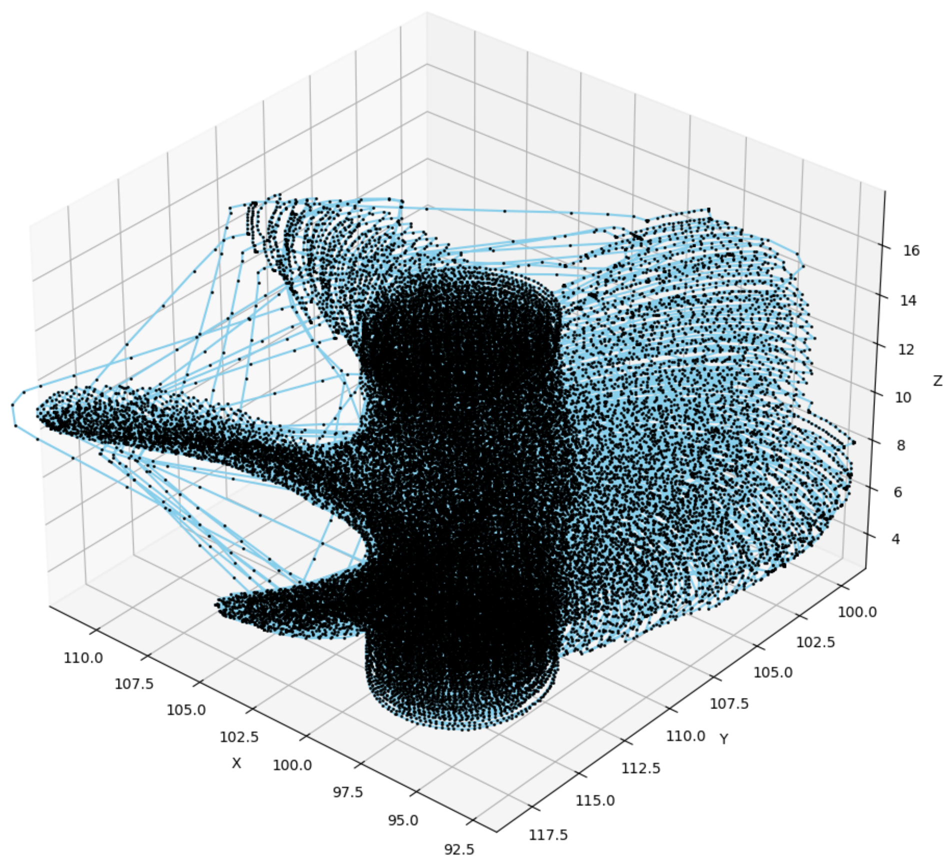


Figure 35 Reverse-Engineered Component: Propeller

This is the point cloud of the tool head position throughout the manufacturing process which can be used to re-engineer the actual product and do post process analysis of the same.

The next component taken in consideration is a turbine. The CAD design of the Turbine is as can be seen below.

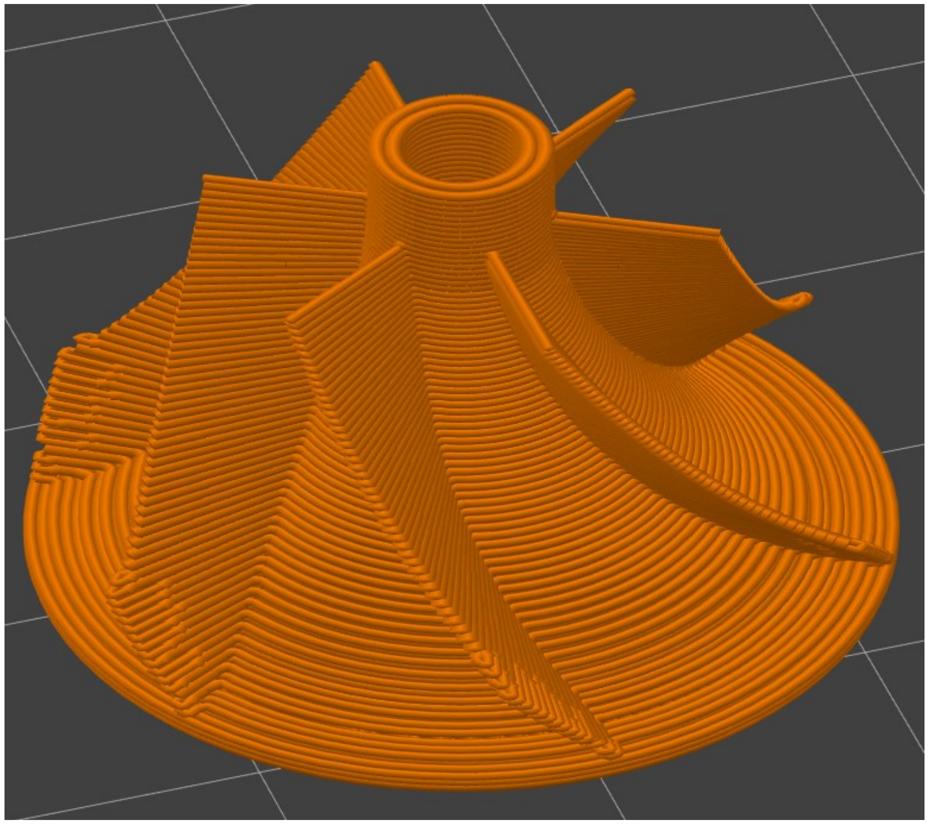


Figure 36 CAD Design for Turbine

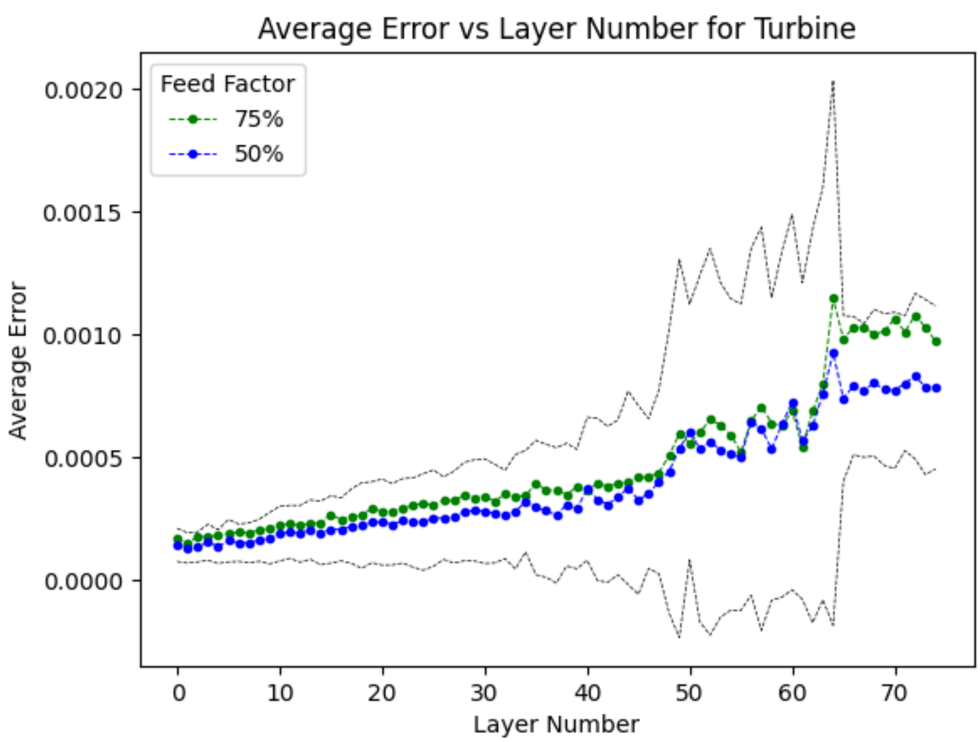


Figure 37 Baseline Error Pattern for Turbine at different Feed Factors

The baseline error plot developed for a Turbine structure is **Figure 37**

here we can see that even by varying the Feed factor, structure of the baseline error plot remains same but the magnitude of the average error slightly increases as the error are increaser with increasing the Feed Factor.

The post-process analysis of the turbine to reverse engineer the developed Turbine structure with the help of data collected from DCS can be seen in the plot below. Here we can do the analysis once the process is complete as well.

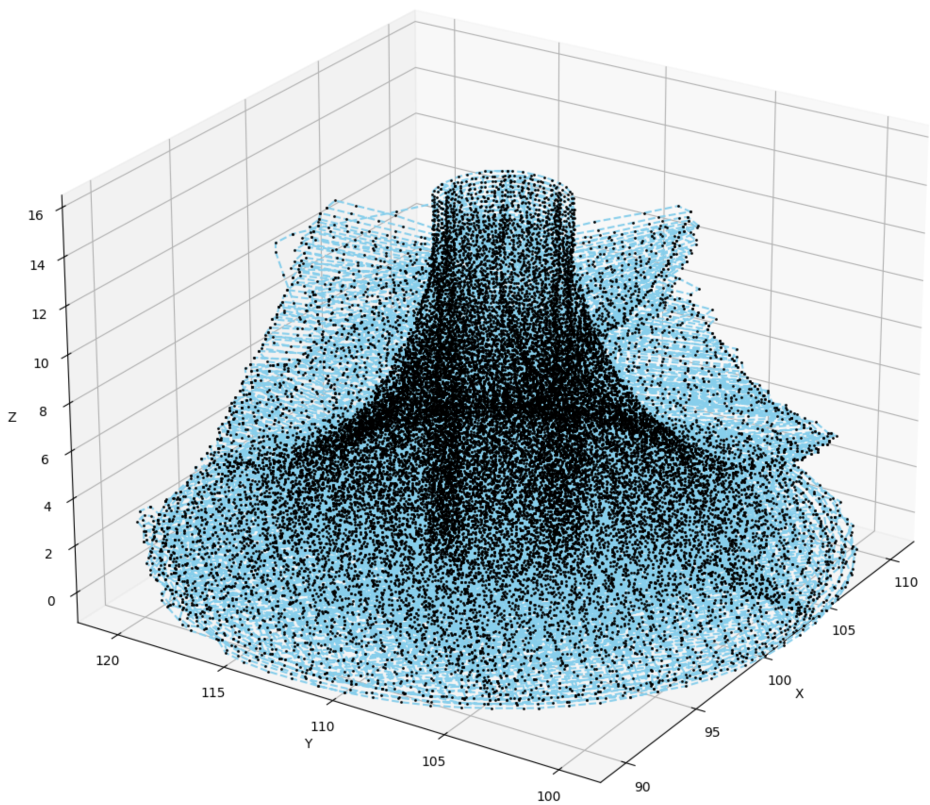


Figure 38 Reverse-Engineered Component: Turbine

In this way the development and validation of the Data collection system is done with different experiments by varying different process parameters such as layer height, Feed Factors for different shape, size and structure of the components as discussed in this chapter.

Chapter 6 Conclusion & Future Scope

This research work has successfully advanced the development of a Cyber-Physical Production environment for Additive Manufacturing system standardized with ISO 23704. It helps to integrate with the PLM lifecycle of the Additive manufacturing products providing a robust framework for integrating Additive Manufacturing systems into large-scale production lines for customized manufacturing.

The key innovation from this research lies in the manufacturing section of the Additive manufacturing lifecycle for the system's capability for real-time monitoring and decision-making. This advancement is a critical component for realizing the full potential of AM in Industry 4.0 applications, where the integration of digital and physical systems is important. Real-time monitoring allows for continuous observation of the manufacturing process. This data is then analysed on-the-fly to take informed decision-making processes that can adjust the AM operations in real-time, ensuring optimal performance and quality. The current implementation focuses on desktop Fused Deposition Modelling machines, but it can also be implemented to different other AM processes as well.

Additionally, the development of a Data Collection System has been a noteworthy achievement. This DCS is not only integral to the real-time monitoring and decision-making capabilities of the Smart Additive Manufacturing system but also plays crucial part in post process analysis of the manufactured components. The post-process analysis facilitated by the DCS allows manufacturers to scrutinize the completed components in detail, identifying any deviations from the desired specifications and understanding the root causes of these variations. This thorough analysis is essential for process optimization, as it provides a clear picture of how different parameters and machine settings affect the final product. By examining the data collected during the manufacturing process, manufacturers can fine-tune the parameters to achieve optimal results, ensuring that each component meets the required quality standards.

Furthermore, the research highlights the importance of standardization, as ISO 23704 provides a structured approach that ensures compatibility and interoperability across different AM systems. The replicability of the system was validated by implementing the system on different FDM machines. This standardization is vital for widespread adoption and integration of Smart Additive Manufacturing system in various industrial sectors. By adhering to established standards, the SAMS can be easily integrated into existing manufacturing infrastructures, facilitating a smoother transition from traditional manufacturing methods to advanced AM technologies.

The future scope of this research is extensive and multifaceted. Several key areas warrant further exploration and development:

- Expansion to Metal Additive Manufacturing: While the current system is designed for desktop FDM machines, there is significant potential for adapting the technology to metal additive manufacturing processes, such as Wire-Arc Additive Manufacturing (WAAM). Given the similarities in the manufacturing processes, extending the Smart AM system to WAAM could greatly enhance its applicability and utility in the production of metal components. This would involve developing specialized algorithms and control mechanisms tailored to the unique requirements of metal AM, ensuring optimal performance and quality in metal part production.
- Scalability and Integration: Further work is needed to scale the system for use in larger and more complex production environments. This includes enhancing the DCS to handle a broader range of AM technologies and integrating it with existing industrial automation systems to ensure seamless operation across various manufacturing platforms. Developing modular and scalable solutions will enable the Smart AM system to be customized for different production scales, from small batch productions to large-scale manufacturing facilities.

- Advanced Monitoring and Analytics: Developing more sophisticated monitoring and analytics capabilities will be essential for advancing the Smart AM system. This includes leveraging advanced sensor technologies and machine learning algorithms to improve real-time decision-making and predictive maintenance capabilities. By incorporating advanced data analytics, the Smart AM system can provide deeper insights into the manufacturing process, enabling proactive identification and resolution of potential issues before they impact production quality or efficiency.
- Developing a Behaviour Model Compliant with ISO 23704: Creating a behaviour model of the AM workflow that complies with ISO 23704 standards is a crucial step forward. This will involve developing a detailed model of all the stages of AM process to generate value added data about abnormalities in the AM process and rigorously testing it. Compliance with these standards will ensure that the system maintains high levels of reliability, safety, and interoperability with other standardized systems.
- Future work will also include creating a prediction model for surface roughness (Ra) to improve quality control. This will involve collecting and analysing data on surface roughness, identifying key influencing factors, and developing a model that can accurately predict Ra based on these factors. By accurately predicting surface roughness, manufacturers can better control the quality of their products, reducing the likelihood of defects and enhancing the overall performance of the AM process. This predictive capability will be particularly valuable in applications requiring high precision and stringent quality standards, such as in aerospace, automotive, and medical device manufacturing.
- User Interface and Usability: Enhancing the user interface and usability of the system will be crucial for broader adoption. This involves developing intuitive interfaces and user-friendly tools that facilitate easy operation and integration into existing workflows.
- Cross-Industry Applications: Exploring the potential applications of the CP-PLM for AM across different industries can open up new opportunities for

innovation and growth. There is potential for the Smart AM system to be applied in areas such as construction, healthcare, and consumer goods. Customizing the Smart AM systems to meet the specific needs and challenges of these industries can further drive its adoption and impact.

By addressing these future directions, the Smart Additive Manufacturing system can continue to evolve, driving innovation and efficiency in the manufacturing industry and solidifying its role in the era of Industry 4.0. The ongoing development and refinement of the SAMS will ensure that it remains a cutting-edge solution, capable of meeting the diverse and ever-changing demands of modern manufacturing.

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