COLLABORATIVE PLATFORM FOR STANDARDIZED DIGITAL TWIN DEVELOPMENT FOR ASSET LIFE CYCLE MANAGEMENT

M.Tech. Thesis

by

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A THESIS

Submitted in the partial fulfillment of the

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of

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **"COLLABORATIVE PLATFORM FOR STANDARDIZED DIGITAL TWIN DEVELOPMENT FOR ASSET LIFE CYCLE MANAGEMENT"** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DEPARTMENT OF MECHANICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my work carried out during the period from July 2023 to June 2025 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.

09/06/2025

Signature of the student with date

GAJULA THUMMALA MANOJ KRISHNA

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

Signature of the Supervisor of M.Tech Thesis

DR. VIBHOR PANDHARE

GAJULA THUMMALA MANOJ KRISHNA has successfully given his M.Tech. Oral Examination held on **26/05/2025**.

Signature of the Supervisor of M.Tech. thesis

Date: 9/6/2025

Convener, DPGC

Date: 9/6/2025

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ABSTRACT

The manufacturing sector has experienced a revolutionary shift in the last few decades, transforming from established, mechanized production systems to highly connected digital networks of advanced technology. The key to this revolution is the digitalization of physical systems, processes, and assets, a paradigm shift that has transformed the way industries design, produce, monitor, and maintain. Industry 4.0 is defined by the shift to the Internet of Things (IoT), artificial intelligence (AI), machine learning, big data analytics, cloud computing, and industrial robotics. Central to this revolution is the Digital Twins concept.

Digital Twin technology has been widely applied across many industrial sectors. and that says a lot about how multifaceted and revolutionary it is. In manufacturing, Digital Twins allow for predictive maintenance by continuously monitoring the health of equipment and forecasting potential failures ahead of time, so there is reduced unplanned downtime and maintenance expense.

Although Digital Twin technology has huge potential and is increasingly being employed, there remain many challenges that stand in the way of its widespread adoption and fullest use. The most intrinsic challenge is probably data integration and interoperability. In a typical factory environment, operational data, design specifications, maintenance history, and human expertise are generally spread across many different platforms and systems, very seldom gathered into one database. Lack of standardization is the second grand challenge. While standards like ISO 23247 offer reference architectures for developing Digital Twins, the implementation styles are immensely divergent in organizations and industries. Not having common standards hinders receiving seamless integration among multiple systems and stakeholders, which ultimately restricts the scalability and effectiveness of Digital Twin solutions. The complexity of multi-stakeholder collaboration is of a nature that organizations struggle to manage. Creating a Digital Twin typically involves input from a variety of domain experts, like product managers, design engineers, data acquisition engineers, data scientists, maintenance operators, and manufacturing engineers. Each contributor brings something unique, with diverse requirements and expertise. It is a major challenge to coordinate their activities and provide good communication.

This study offers a structured, collaborative Digital Twin development framework per the ISO 23247 architecture for use in enabling asset management within diverse industrial applications. A scalable Digital Twin Setup Tool has been implemented based on an Excel-based interface,

which captures domain experts' static and dynamic information systematically, ranging from product managers, design engineers, and data acquisition engineers to data scientists. The resultant platform fills the gap in implementation between theoretical Digital Twin architecture and actual deployment, providing a cost-effective, easy-to-use solution with asset lifecycle tracking and stakeholder collaboration support. It creates the foundation for enhanced analytics like Remaining Useful Life (RUL) estimation and decision support, and as such, will help promote Digital Twin technologies further within small- to medium-scale manufacturing environments.

The tool was validated on two industry case studies—Go3D Artish 700 and Ball Screw Assembly—where it successfully consumed real-time data streams and developed dynamic, role-based dashboards. The dashboards enabled actionable insights for stakeholders such as product managers and technical supervisors, providing continuous visibility into machine health, utilization trends, and forecasted maintenance events.

The modular and integratable nature of the tool ensures versatility in industry and technical competence levels. In summary, the proposed Digital Twin platform is an important step forward in digital manufacturing with a highly potent, standardized, and scalable solution firmly in tune with Industry 4.0 objectives and capable of future-proofing intelligent decision-making and asset life cycle management.

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ABBREVIATIONS

ISO	International Standard Organization
ML	Machine Learning
DT	Digital Twin
PS	Physical System
DS	Digital System
P2V	Physical to Virtual
V2P	Virtual to Physical
OPT	Optimization
RF-LSTM	Random Forest – Long Short Term Memory
PCA	Principal Component Analysis
OME	Observable Manufacturing Element
CNC	Computer Numerical Control
CAD	Computer-Aided Design
CSV	Comma-Separated Value
KF	Kalman Filter
IMU	Inertial Measurement Unit
RTF	Run To Failure
CPU	Central Processing Unit
GPU	Graphical Processing Unit
DAQ	Data Acquisition

KPI	Key Performance Indicator

Chapter 1 - Background

1.1 History

The manufacturing industry has undergone a revolutionary transformation in the past few decades, shifting from traditional, mechanized manufacturing systems to advanced, highly interconnected digital networks. It has been driven by the relentless pursuit of operational effectiveness, improvement in quality, and competitiveness in an increasingly globalized economy. [1] The focal point of this revolution is the digital representation of the physical systems, processes, and assets, a paradigm shift that has revolutionized how industries design, manufacture, monitor, and maintain.

Industry 4.0 is a term that was first employed in Germany in the year 2011, referring to the convergence of information technology (IT) and operational technology (OT) to create intelligent manufacturing environments in which the virtual and the physical worlds are interconnected on an ongoing basis. It is characterized by the transition to the Internet of Things (IoT), artificial intelligence (AI), machine learning, big data analytics, cloud computing, and industrial robotics. At the heart of this revolution is the concept of Digital Twins.

1.2 Digital Twin

Smart Manufacturing integrates IoT, AI, and automation to create intelligent factories, while Smart Maintenance ensures these systems operate efficiently through the use of predictive analytics and self-healing machines. Digital Twins bridge these two concepts by simulating real-time machine behavior, predicting equipment failures, and displaying the machine's health status. *A Digital Twin is a virtual representation of a physical system (and its associated environment and processes) that is updated through the exchange of information between the physical and virtual systems.*

1.3 Applications for Digital Twin Technology

Digital Twin technology has been extensively used in numerous industrial areas, as mentioned in Figure 1, and that speaks volumes about how versatile and transformative it can be. In manufacturing, Digital Twins enable predictive maintenance by constantly tracking the condition of equipment and predicting likely failures in advance, so there is less unplanned downtime and maintenance cost. Process optimization is another key application where Digital Twins simulate different operating conditions to determine optimal parameters to enhance productivity and quality.

In aerospace, Digital Twins are applied throughout the life of an aircraft, from design and testing to monitoring in operation and maintenance scheduling. Automotive manufacturers apply Digital Twins to virtual prototyping, crash testing, and supply chain optimization.

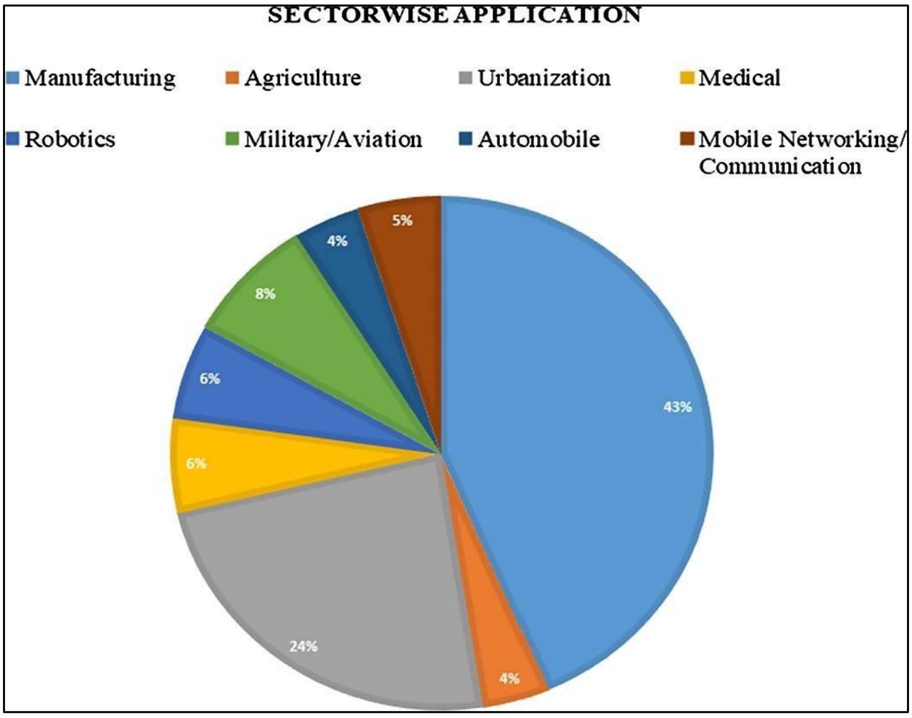


Figure 1: Pie Chart of digital twin-based data analysis paradigm based on the Sector observed in recent papers [2]

Digital Twins are applied in smart cities to design urban development, traffic management, and monitor infrastructure. The building industry employs Building Information Modeling (BIM) as a form of Digital

Twin to represent projects graphically, plan resources, and manage facilities.

Applications in healthcare involve patient-specific Digital Twins for personalized treatments, optimization of medical devices, and managing hospital workflows. The energy sector applies technology to power plant optimization, operation of renewable energy systems, and analysis of grid stability.

1.4 Current Challenges in Digital Twin Implementation

Despite the immense potential and growing use of Digital Twin technology, numerous challenges persist to hinder its mass adoption and maximum utilization. The most inherent challenge is likely data integration and interoperability. In typical manufacturing environments, operational data, design parameters, maintenance records, and human intuition are typically distributed across multiple platforms and systems, rarely consolidated into a single database. This splitting creates huge challenges in developing comprehensive DTs that accurately capture the complexity of physical assets and their world of operation.

The lack of standardization is the second major challenge. Though standards such as ISO 23247 provide reference architectures for building Digital Twins, the styles of implementation are very different in organizations and industries. The absence of shared standards prevents receiving smooth integration among multiple systems and stakeholders, which ultimately limits the scalability and efficiency of Digital Twin solutions.

Data dependability and quality are persistent concerns in Digital Twin implementations. The accuracy of DTs heavily depends on input data quality from various sources, including operating systems, sensors, and human inputs. Inconsistent data formats, missing information, faulty sensors, and human errors can significantly reduce the fidelity and reliability of Digital Twin models.

The complexity of multi-stakeholder collaboration is of a kind that organizations find challenging to manage. Creating a Digital Twin typically involves input from a variety of domain experts, like product managers, design engineers, data acquisition engineers, data scientists, maintenance operators, and manufacturing engineers. Each contributor brings something unique, with diverse requirements and expertise. It is a major challenge to coordinate their activities and provide good communication.

Technical challenges are due to computational complexity, processing needs in real time, cybersecurity, and the need for a robust communication infrastructure. The integration of physical systems and digital ones brings new vulnerabilities that must be addressed to enable data security and system integrity.

1.5 Research Motivation

These problems highlight the imperative requirement of standardized methodologies of Digital Twin development that can bridge the gap between the theoretical frameworks and the practical application. ISO 23247 provides a general reference architecture of DTs, yet there remains a huge implementation gap to transform this standard into practical instruments for facilitating collaboration among various stakeholders and automating the task of creating Digital Twins.

This research addresses this gap by developing a Digital Twin Setup Tool as a holistic platform for consolidating all the information and decisions concerned with Digital Twin development in one usable location. The tool is designed to transform the traditional piecemeal approach to Digital Twin development into a structured, standardized process consonant with ISO 23247 architecture, and be pragmatic and user-oriented for domain experts.

The primary intent of this research is to create a methodology and tool that enables organizations to systematically capture, organize, and make use of the multi-faceted data required for Digital Twin building, including physical assets, environmental conditions, operational information, and human interventions—all combined in an integrated platform enabling good stakeholder collaboration and total coverage of all the DT factors.

In pursuing this research, we aim to contribute to the further maturity of Digital Twin technology by offering a pragmatic approach to addressing real-world application issues and yet remaining faithful to global standards already established. The development of such a tool itself is a breakthrough in the democratization of Digital Twin technology and making access possible for organizations to utilize the value of Industry 4.0 transformation.

1.6 Literature Review

This section gives us a brief introduction to the literature that is currently available for developing digital twins using a specific architecture in the manufacturing industry. Keywords used in this literature review are Digital Twin, Fault Detection, Smart Manufacturing, Predictive Maintenance, ISO 23247, ISO 23704, Condition Monitoring, and ML Algorithms.

The concept of Digital Twin was initially introduced by Michael Grieves in 2002 at the University of Michigan, initially termed as "Mirrored Spaces Model" before evolving into the contemporary Digital Twin terminology. Grieves conceptualized Digital Twin as a virtual representation of a physical product that contains all information required to describe and simulate the physical counterpart. This foundational work established a three-dimensional model comprising the physical space, the virtual space, and the connections between them.

NASA further developed the DT concept for spacecraft health management and mission planning, defining it as an integrated multi-physics, multi-scale, probabilistic simulation that uses the best available physical models, sensor updates, and fleet history to mirror the life of its corresponding flying twin. This aerospace application demonstrated the potential for DTs to enable performance optimization, predictive maintenance, and risk assessment in complex systems.

The evolution of DT technology has been significantly influenced by advances in Internet of Things (IoT), artificial intelligence, machine learning, and cloud computing. These technological convergences have enabled real-time data acquisition, processing, and analysis capabilities that are essential for maintaining synchronization between physical and digital representations.

Recent literature has established various classification frameworks for Digital Twin implementations. [12] Onaji et al. (2022) developed a comprehensive framework for Digital Twin implementation in manufacturing environments, focusing on flexibility and integration aspects. Their research carried out a thorough literature review to examine the potential of the digital twin concept as an integrated platform to promote scalability, flexibility, and integration in the manufacturing industry, providing flexibility that allows systems to easily adapt to changes in product requirements.

[13] Attaran et al. (2023) investigated the transformative impact of Digital Twins on intelligent manufacturing and Industry 4.0 evolution. Their research demonstrated that in the past few years, Digital Twins have dramatically reduced the cost of developing new manufacturing approaches, improved efficiency, reduced waste, and minimized batch-to-batch variability. The study highlights the evolution of Digital Twins and reviews enabling technologies while identifying implementation challenges.

[14] Soori et al. (2023) provided a comprehensive review of Digital Twin applications specifically in smart manufacturing contexts. Their research demonstrated that the application of digital twins in smart manufacturing can reduce time to market by designing and evaluating manufacturing processes in virtual environments before manufacture, presenting comprehensive simulation platforms to simulate and evaluate product performance.

[15] Xu, Zhang et al. (2024) presented a comprehensive analysis of Digital Twin research trends through a systematic examination of 4,954 articles from the Web of Science database spanning 2014-2024. Their research visually dissects digital twin literature, leveraging keyword cluster analysis to identify focal areas that have captivated researchers in recent years, along with prevailing research trends. The study provides strategic recommendations for the evolutionary trajectory of Digital Twin technology.

[16] Son et al. (2022) conducted a temporal analysis of Digital Twin development in smart manufacturing, examining the technology's evolution from early concepts to future applications. Their research focused on the Fourth Industrial Revolution era, emphasizing the growing focus on digital twin technology to advance toward smart manufacturing. The study provides insights into the technological trajectory and future research directions

The integration of Digital Twin technology within Industry 4.0 frameworks has been extensively studied in recent literature. [17] Tao et al. (2020) demonstrated how Digital Twins serve as enabling technologies for cyber-physical systems (CPS), facilitating seamless integration between operational technology and information technology domains. Their work highlighted the importance of Digital Twins in achieving smart manufacturing objectives through real-time monitoring, predictive analytics, and autonomous decision-making capabilities.

[18] Qi et al. (2021) explored the role of Digital Twins in smart manufacturing ecosystems, emphasizing their contribution to mass customization, flexible manufacturing, and supply chain optimization. Their research demonstrated how Digital Twins enable manufacturers to respond rapidly to market changes while maintaining operational efficiency and product quality.

The concept of Digital Thread, as discussed by [19] Forward et al. (2021), represents the evolution of Digital Twin technology toward comprehensive product lifecycle management. Digital Thread encompasses the entire product journey from design and manufacturing through operation and end-of-life, providing continuous data connectivity and traceability across all lifecycle phases.

The development of international standards for Digital Twin implementation has been a critical focus area in recent literature. ISO 23247 series, published in 2021, represents the first comprehensive international standard specifically addressing Digital Twin frameworks for manufacturing systems. The standard establishes reference architecture, data models, and implementation guidelines that ensure interoperability and consistency across different Digital Twin implementations.

[3] Thelen et al. (2024) propose a five-dimensional digital twin model (DT = F(PS, DS, P2V, V2P, OPT)), emphasizing bidirectional data flow between physical and virtual systems. This framework integrates physical systems, digital models, updating engines (P2V), prediction engines (V2P), and optimization (OPT). It also provides a comprehensive review of digital twin technologies, highlighting their transformative potential across industries. However, challenges in data, modeling, integration, and scalability must be addressed to unlock their full potential. Future research should focus on hybrid modeling, real-time data, federated learning, and scalable architectures to bridge these gaps.

[4] Söderberg et al. (2017) discuss the implementation of a Digital Twin for real-time geometry assurance in automated production. Geometry assurance minimizes geometrical variations affecting product quality across design, pre-production, and production phases. Digital Twins leverage simulation, optimization, and real-time data to enhance production efficiency and quality. Key functionalities include locating scheme optimization, statistical variation simulation, inspection preparation, and root cause analysis. The approach supports a shift from mass production to individualized production, addressing geometry-related cost issues effectively.

[5] Ogunsanyaa et al. (2022) focus on utilizing deep learning (multilayer perceptron) to predict output parameters (dimensional accuracy, porosity, tensile strength) in Fused Deposition Modeling (FDM). The methodology used was to conduct fractional factorial design experiments with five input parameters (layer thickness, extrusion temperature, etc.) across 243 data points. And found out that Optimal hyperparameters were identified, revealing that learning rates and hidden layers significantly impact model performance. Emphasizes the need for balancing prediction accuracy and computational efficiency for real-time applications

[6] Kun et al. (2018) focus on the Objective to diagnose faults in delta 3D printers using attitude sensors and Support Vector Machines (SVM). The Methodology used was to use Attitude sensors to monitor 3-axial angles, angular velocity, and vibrations; data collected under 12 fault types and normal conditions. Results obtained are that SVM achieved a fault diagnosis accuracy of 94.44% using all sensor channels; comparison with Back Propagation Neural Network (BPNN) showed inferior performance. The proposed method effectively monitors printer health and enhances fault detection, crucial for maintaining print quality.

[7] Li et al. (2024) focus on the Objective to analyze molten pool dynamics and predict cladding layer height in Laser Direct Energy Deposition (L-DED). Some key findings are defining the molten pool overflow (MPO) phenomenon through theoretical and numerical models. Developing a numerical-assisted RF-LSTM prediction model to enhance cladding layer height accuracy. Experimental validation showed a significant correlation between MPO features and cladding quality. Implications occurred are Insights can optimize L-DED processes, improving part quality and stability.

[8] Yao, Xifan, et al. (2019) explore the integration of Cyber-Physical Systems (CPS) in smart manufacturing, linking it to Industry 4.0. Introduces models like cloud manufacturing, social manufacturing, and wisdom manufacturing. Proposes an eight-tuple model for CPS-based

manufacturing, extending to a nine-tuple for wisdom manufacturing. Highlights real-time data access, reconfigurability, decentralized decision-making, and enhanced intelligence. Emphasizes the need for integrating social aspects in manufacturing for innovation and sustainability.

[9] Thoben et al. (2017) review the fourth industrial revolution, focusing on Industrie 4.0 and smart manufacturing. It highlights the integration of the Internet of Things (IoT) and cyber-physical systems (CPS) in manufacturing. Key initiatives include Germany's Industrie 4.0 and the U.S. smart manufacturing programs. The paper discusses application scenarios, challenges, and future research issues in technology, methodology, and business models. Emphasis is placed on enhancing human-robot collaboration and developing new business strategies for competitive advantage.

[10] Pandhare Vibhor et al. (2022) discuss a two-phase methodology for monitoring the health of ball screws in industrial applications using inertial sensors. Ball screws are critical components in linear positioning systems, and their degradation can lead to the loss of accuracy and reliability in production systems. The proposed approach addresses limitations in existing monitoring methods by combining online fault detection and offline fault quantification. An RTF experiment was conducted on a linear-axis testbed. Data was collected continuously over 8693 hours of operation, with periodic interruptions for Phase II measurements. Results showed that the proposed method effectively detected faults and quantified backlash changes, with significant backlash observed at 8000 hours of operation. The PCA-T2 method was compared with other state-of-the-art techniques (e.g., Gaussian Mixture Model, Self-Organizing Maps, Isolation Forest, Auto-Encoder). PCA-T2 was preferred for its simplicity and consistent results. Backlash was estimated using signal position shifts and perceived ball screw pitch changes. Both methods showed similar trends, with backlash increasing to approximately 10 μm at 8000 hours. The two-phase methodology provides a robust solution for early detection and backlash

quantification, reducing downtime and enabling predictive maintenance in production systems.

[11] Kumar et al. (2018) explore the integration of Industry 4.0 concepts into maintenance practices, termed Maintenance 4.0, and highlight the challenges and opportunities associated with this transformation. It also emphasizes the importance of Maintenance 4.0 in achieving Industry 4.0 goals, enabling smarter, more efficient manufacturing processes.

1.7 Research Gaps and Opportunities

The literature review reveals several critical gaps in current Digital Twin research and implementation approaches. While theoretical frameworks and reference architectures are well-established, there remains a significant lack of practical tools and methodologies that facilitate systematic Digital Twin development. Most existing research focuses on individual case studies or specific application domains, with limited attention to generalizable implementation approaches.

The collaboration aspects of Digital Twin development remain underexplored, particularly in terms of structured methodologies for multi-stakeholder engagement and coordination. Current literature lacks comprehensive frameworks for integrating diverse domain expertise and managing complex stakeholder relationships throughout the Digital Twin development lifecycle.

Furthermore, the translation of international standards such as ISO 23247 into practical implementation tools represents a significant research opportunity. While the standard provides comprehensive architectural guidance, there is limited research on systematic approaches for standard compliance and practical tool development that facilitates standard adoption across diverse industrial contexts

1.8 Objectives

This study aims to fill a gap in the literature by analyzing and standardizing the DTs. It also focuses on the resources and their location, required by different domain experts to develop a DT. At last, validate the developed tool for the creation of the DT on two different case studies (Go3D Artish 700 and Ball Screw).

1.9 Organization of the Thesis

This thesis contains six chapters. The current chapter provides an introduction and background to the research topic, highlighting its importance, defining key concepts, and outlining the scope of the study. It also focuses on the applications of DTs in different sectors. The challenges occur while implementing digital twins without the ISO standard. It also focuses on a comprehensive literature review, critically analyzing and synthesizing existing research related to the topic, identifying gaps in current knowledge, and stating the research problem and objectives. This chapter will also give a brief overview of the subsequent chapters.

The second chapter will focus on the methodologies and the development of the collaborative platform for standardized digital twins for asset management.

The third chapter will focus on exploring the types of algorithms on a particular dataset and their results, and the scope of the dataset for further use.

The fourth and fifth chapters will provide the details of case studies 1 and 2, respectively, and explain the implementation of the DT setup tool. In the end, the results and findings obtained from the research will be presented, utilizing appropriate data visualization techniques, like dashboards, and analyzing the results about the research objectives, highlighting the health aspects of the component.

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 Methodology and Collaborative Digital Twin Setup Tool Development Using ISO 23247

2.1 ISO 23247 Architecture

[22] This architecture defines a framework to support the creation of Digital Twins for observable manufacturing elements, including personnel, equipment, materials, processes, facilities, environment, and products.

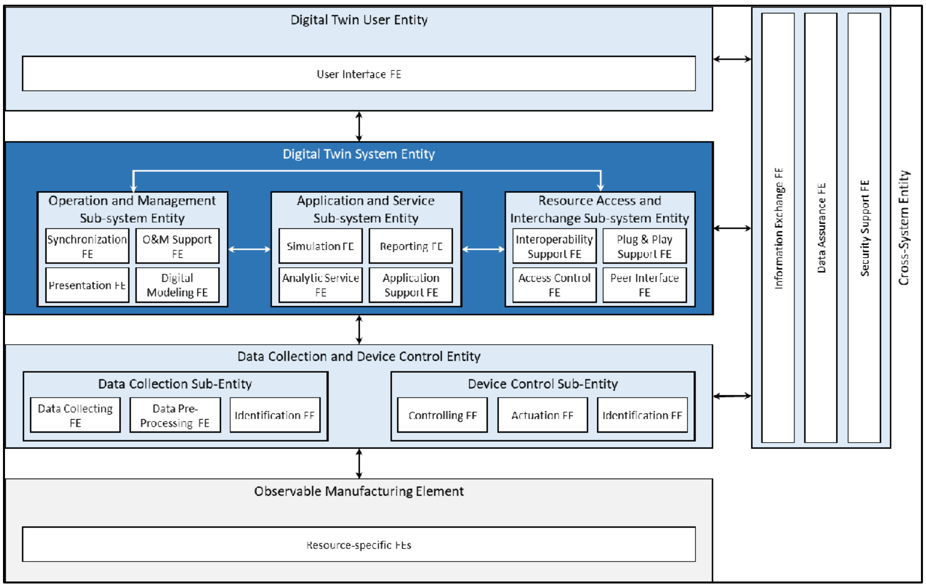


Figure 2: Functional reference architecture of Digital Twin for manufacturing – decomposition of functional entities (FEs)

In the above figure, you can see four major functional entities, namely the Digital Twin User Entity, the Digital Twin System Entity, the Data Collection and Device Control Entity, and the Observable Manufacturing Element.

This research proposes a novel concept of implementing ISO 23247 architecture to create a DT, which is a standard one, that can integrate with other digital twins.

2.2 Methodological Evolution

The research methodology evolved through three distinct phases, each refining the approach based on empirical findings and practical implementation challenges. The initial methodology established a foundational framework for Digital Twin development, focusing on data diagnosis systems for comprehensive dataset analysis, followed by digital twin modeling, machine learning algorithm implementation, and feedback control loop development. This phase provided the essential structure while identifying key areas for improvement.

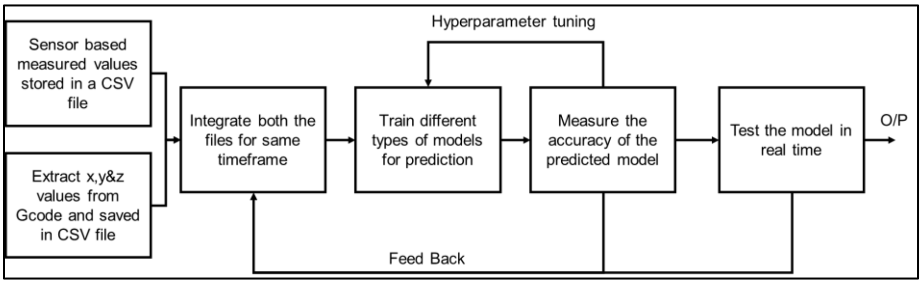


Figure 3: The overall approach to predicting values from the Creality Ender-3 Neo 3D printer dataset.

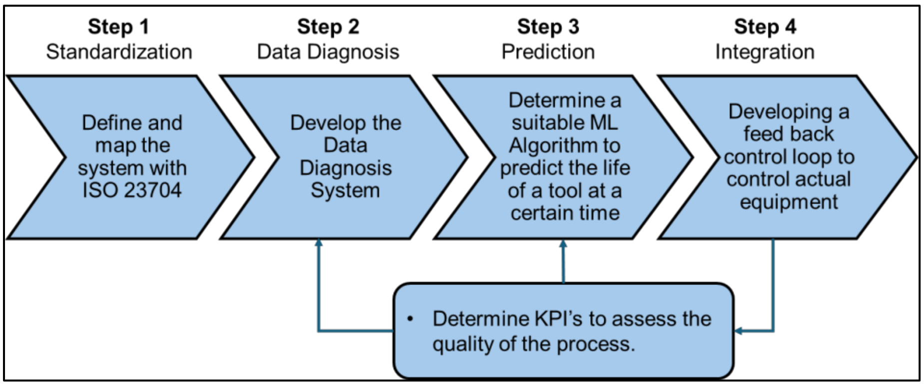


Figure 4: Initial approach for developing the Digital Twin.

Recognizing the need for deeper data understanding, the second iteration introduced Exploratory Data Analysis (EDA) to replace the data diagnosis system, ensuring thorough dataset comprehension before model development. The feedback control loop was also modified to prioritize Digital Twin development with existing datasets, addressing limitations in physical testing environments.

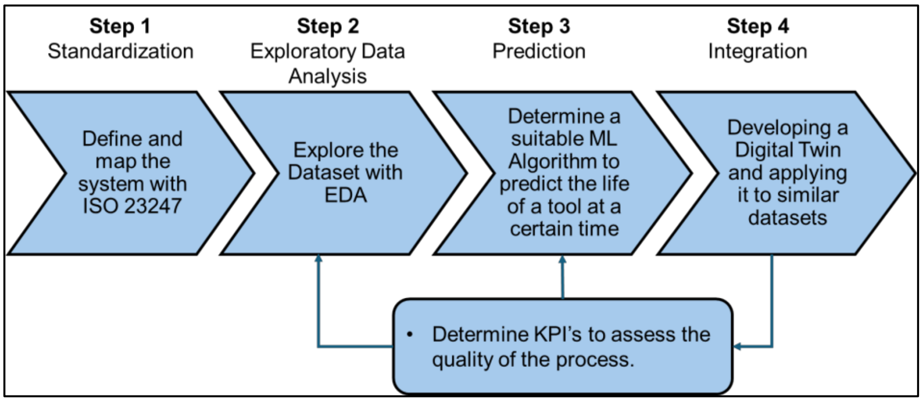


Figure 5: Modified methodology incorporating EDA for enhanced dataset analysis.

The final phase integrated compliance with the ISO 23247 standard, emphasizing international best practices in Digital Twin development. It also introduced a scalable tool to ensure adaptability across diverse industrial applications, forming the basis for the Digital Twin Setup Tool. This refined methodology balanced theoretical rigor with practical implementation, enabling efficient and standardized Digital Twin deployment.

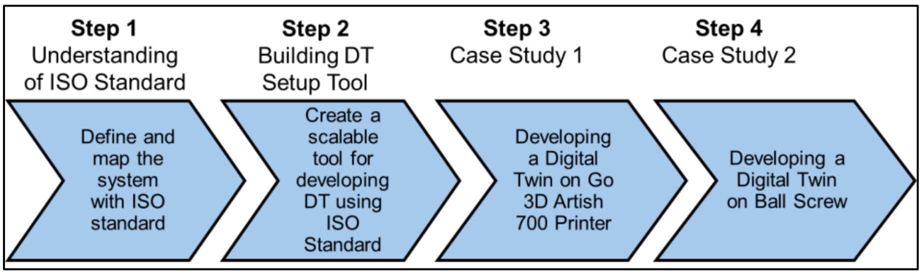


Figure 6: Final methodology incorporating ISO standards and scalable tool development.

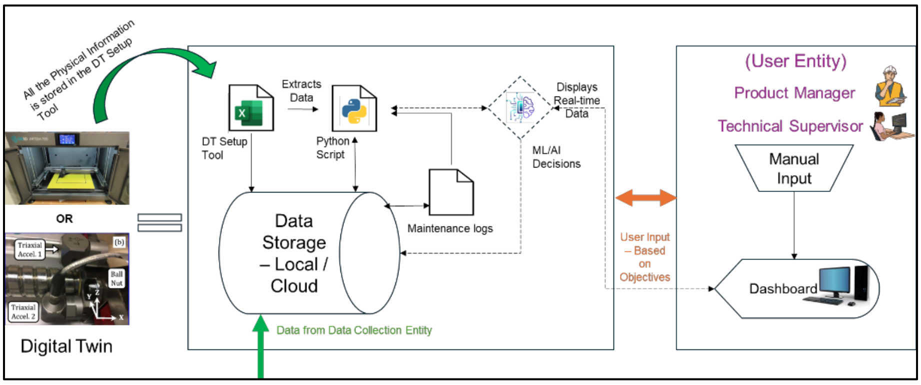


Figure 7: Step-by-step Digital Twin creation process using the DT Setup Tool (Go 3D Artish 700 Printer).

2.3 Digital Twin Setup Tool Development

This section describes the process undertaken to create the Digital Twin (DT) Setup Tool and the resultant Digital Twin according to the ISO 23247 standard.

Prior to engaging in the process of creation, one should know the DT Setup Tool and the resources needed to construct it. In traditional manufacturing practices, the production of a physical asset involves a range of dimensions such as physical components, environmental conditions, operational information, and human decisions. These decisions—typically made by subject matter specialists—are typically spread out across different platforms and rarely consolidated into a single database. DT Setup Tool attempts to bridge this disconnect by bringing together all relevant information and decisions into a single location. It is a single-stop source for materials required for creating a DT.

The table below shows the different dimensions required for the development of a DT of a physical asset. The dimensions are components, conditions/information, decisions, and people. Based on these dimensions the development of physical product occurs, similarly, to build a digital twin the data which is used to develop the physical product, the same is required.

Table 1: Different Dimensions involved in the development of a Digital Twin for a physical asset

Dimension 1 **(Components)**	**Dimension 2** **(Conditions/ Information)**	**Dimension 3** **(Decisions)**	**Dimension 4** **(People)**

3D Printer	Scheduling	Maintenance	Product Manager
CNC Machine	Planning	Operations	Design Engineer
Bearings	Maintenance	Condition Monitoring	Data Acquisition Engineer
Nozzle	Inventory	Production Monitoring	Data Scientist
Extruder	Design Specifications	Process Monitoring	Maintenance Operator
Ball Screw	Signals and Logs	Traceability	Manufacturing Engineer

Figure 8: People involved in the Asset Life cycle

Note: The table has a subset of the components. Numerous others contribute to each dimension.

Figures 8 & 9 depict the different engineers across the asset lifecycle. Each of the domain experts is responsible for contributing to the development of the assets. As described previously, the ISO 23247 architecture provides a reference for DTs whereby each functional entity makes a contribution to modeling the physical system. These functional entities can be directly mapped to the respective domain experts. This enables us to gather all the data required to construct a Digital Twin systematically.

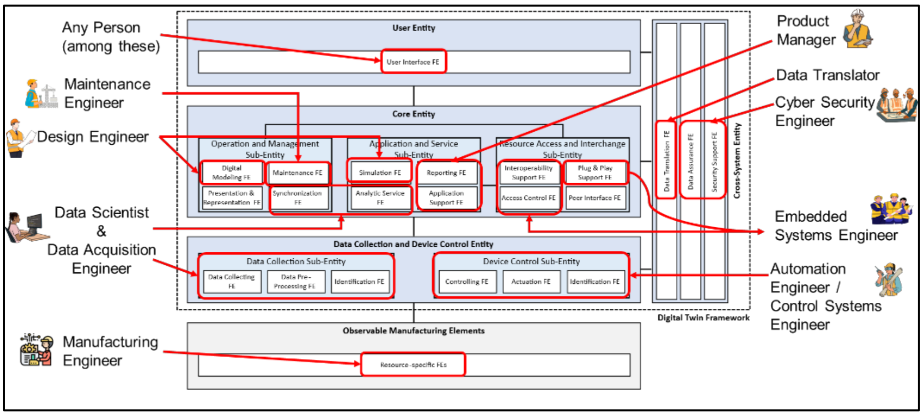


Figure 9: Different Experts sharing the physical data used to manufacture an asset in the digital form as per the ISO 23247 standard to develop the digital twin

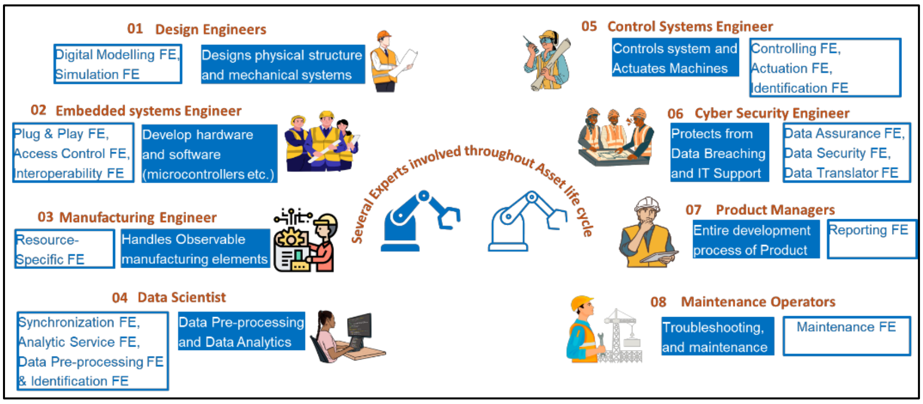


Figure 10: Capturing the information of the Asset using ISO 23247

Figure 10 illustrates how data are extracted from such experts based on ISO 23247 guidelines. Even though ISO 23247 prescribes structural and data flow entities, it does not leave it to be determined how data is captured and stored. For our implementation, we utilized Microsoft Excel as a platform on which to build the DT Setup Tool. Now, let us talk about how we are going to create the digital twin setup tool using ISO 23247 architecture. There are several options to create a digital twin setup tool, like a web interface, a mobile application, an Excel file, etc. Here, an Excel file was used as an option to develop a digital twin setup tool.

The DT Setup Tool in Excel has several sheets. Each sheet is allocated to a particular domain expert, organized according to the ISO 23247 functional architecture.

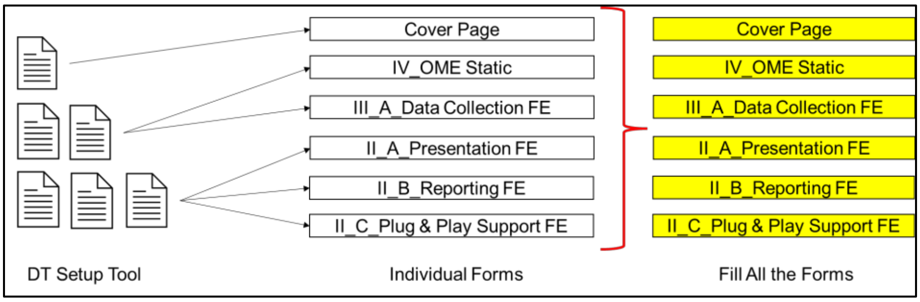


Figure 11: Overview of the sheet structure of the Excel tool, with sheets renamed to reflect the respective domain experts

As shown in the above figure, the names of the sheets are renamed in such a way that it is easy to understand by the domain experts and also based on the reference architecture ISO 23247.

In the above figure, the basic details of the company (user/product manager) and its address are captured, along with its objectives. Entering firm data and project objectives enables the reuse of pre-formatted component templates.

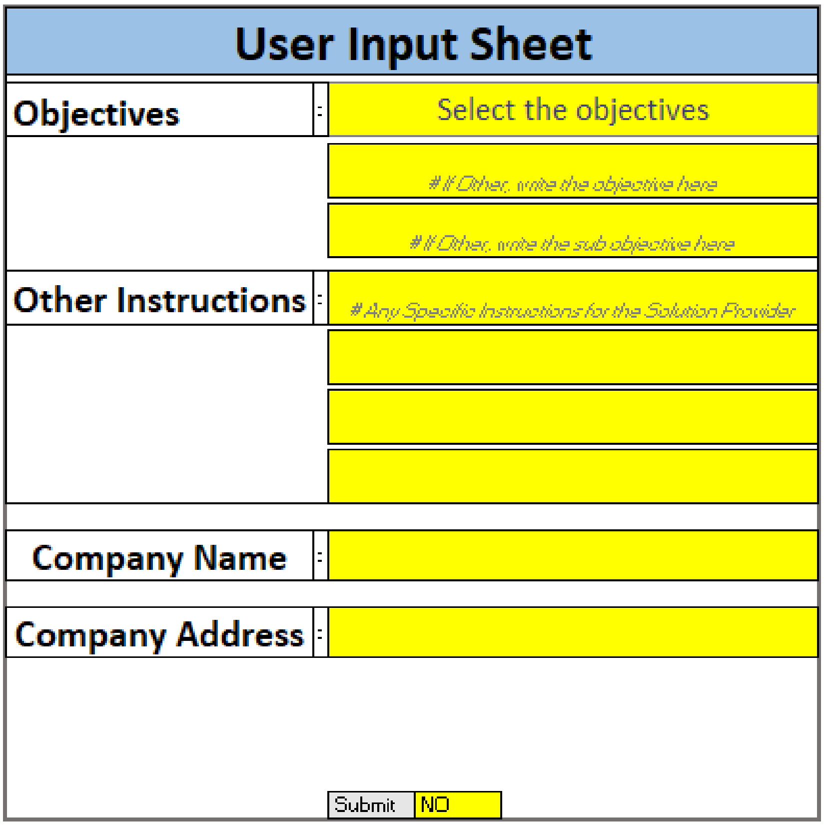
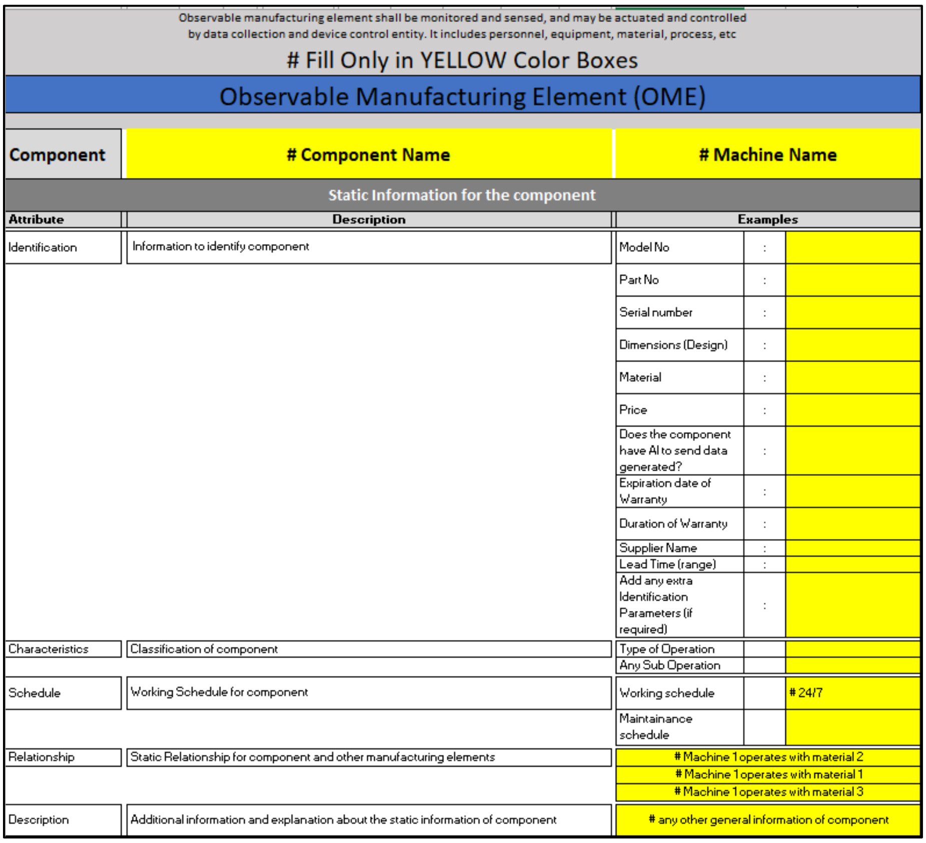


Figure 12: User Input sheet to be filled by the product manager



Observable manufacturing element shall be monitored and sensed, and may be actuated and controlled by data collection and device control entity. It includes personnel, equipment, material, process, etc

Fill Only in YELLOW Color Boxes

Observable Manufacturing Element (OME)

Component	# Component Name	# Machine Name		
Static Information for the component				
Attribute	**Description**	**Examples**		
Identification	Information to identify component	Model No	:	
		Part No	:	
		Serial number	:	
		Dimensions (Design)	:	
		Material	:	
		Price	:	
		Does the component have AI to send data generated?	:	
		Expiration date of Warranty	:	
		Duration of Warranty	:	
		Supplier Name	:	
		Lead Time (range)	:	
		Add any extra Identification Parameters (if required)	:	
Characteristics	Classification of component	Type of Operation		
		Any Sub Operation		
Schedule	Working Schedule for component	Working schedule		# 24/7
		Maintainance schedule		
Relationship	Static Relationship for component and other manufacturing elements	# Machine 1 operates with material 2		
		# Machine 1 operates with material 1		
		# Machine 1 operates with material 3		
Description	Additional information and explanation about the static information of component	# any other general information of component		

Figure 13: Static details of the observable manufacturing elements

Under this structure, the static data related to the physical elements is recorded by the design engineer in a separate sheet. This sheet is used as a master reference that records all the non-changing characteristics associated with the manufacturing environment. The next section is addressed to Observable Manufacturing Elements (OMEs), which cover all the physical equipment used in the industrial environment. They include but are not limited to CNC machines, industrial robots, motors, ball screws, and 3D printers.

Every OME relates to suitable sensors and actuators for bidirectional communication between the physical and the digital worlds. Sensors are used to acquire data from these devices, whereas actuators react to decisions by either the user or the digital twin system itself. Recordings of these OMEs are important because they provide an extensive insight into the operational workflow and dynamic behavior of the shop floor. This methodical depiction of the physical objects serves as the foundation for creating smart monitoring, control, and decision-making capabilities within the digital twin framework.

Dynamic Information				
Attribute	**Description**	**Examples**		
Status	Performance aspects of the component	Products (output)		mm
		Pressure		kWh
		Noise		W
		Extra Load (kgs)		C
		Pitch		# dB
		Vibration	# 10	# mm
		Pitch		mm
		Backlash		
		Torque		Nm
		Extra Load (kgs)	# 100	# kgs
		Pressure		Mpa
Location	Location information (geographical / relative location)	# Machine 2 at Work unit 2 in Room 3		
		# Machine 2 at Work unit 1 in Room 2		
		# Machine 2 at Work unit 2 in Room 2		
Report	Working report related to component	# May 14th, 2019 9 AM to 6PM: Regular Maintenance		
		# May 14th, 2019 11 AM: Machine #1 reports high temperature		
Relationship	Dynamic Relationship for component and other manufacturing elements	# Machine 1 operates with material 2 by Operator 3 at Workunit 2		
Description	Additional information and explanation about the dynamic information of component	# Dynamic information of component changing during manufacturing processes		

Figure 14: Dynamic details of the observable manufacturing elements (OMEs)

In the above figure, dynamic details refer to the values that change over time. This information is highly important to understand the dynamic behavior of the physical asset.

Process	Type of Operation	# Component Name		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Information to identify Process	Process Identifier		
Characteristics	Classification of component	Production		
		Maintenance		
		Quality Test		
		Inventory		
		Milling		# To and Fro
		Drilling		
		Additive		
Schedule	Working Schedule for Process	Periodic		One time
		duration	3	hours
		Runs	90	Nos
		Pause time	10	Sec
		Frequency	3	days
		Speed	20	mm/sec
			100	mm/sec
			500	mm/sec
		Travel	450	mm
Relationship	Static Relationship for process and other manufacturing elements	# Manufacturing Process 1 is Managed by a Person 2 with Skill3		
Description	Additional information and explanation about the static information of process	# Any other general information about process		

Figure 15: Static details of the operation that is involved with the physical asset

Figure 15 shows the static information on the physical assets' operations. It is necessary to capture this data since the performance of a physical asset depends largely on what operation it is performing. Varying manufacturing processes have different effects on important operational parameters of the physical component. Hence, it becomes important to capture and track the operation being conducted, as it has a direct influence on the behavior of the asset, its performance characteristics, and lifecycle. Information acts as a basis for proper modeling, analysis, and decision-making in the DT environment.

Dynamic Information		
Attribute	**Description**	**Examples**
Status	Status of the Process	Planned
		In-Process
		Stopped abruptly
Location	Location information (geographical / relative location)	# Process 1, Machine 2, Room 3
Report	Working report related to process	# May 14th, 2019: Machine #2 completed MillingOperation #5.
Relationship	Dynamic Relationship for process and other manufacturing elements	# MillingOperation #1 is operated by Person #3 with Skill #2 in WorkCenter #3
Description	Additional information and explanation about the dynamic information of process	# Dynamic information of component changing during manufacturing processes

Figure 16: Dynamic information of the operation that is involved with the physical asset

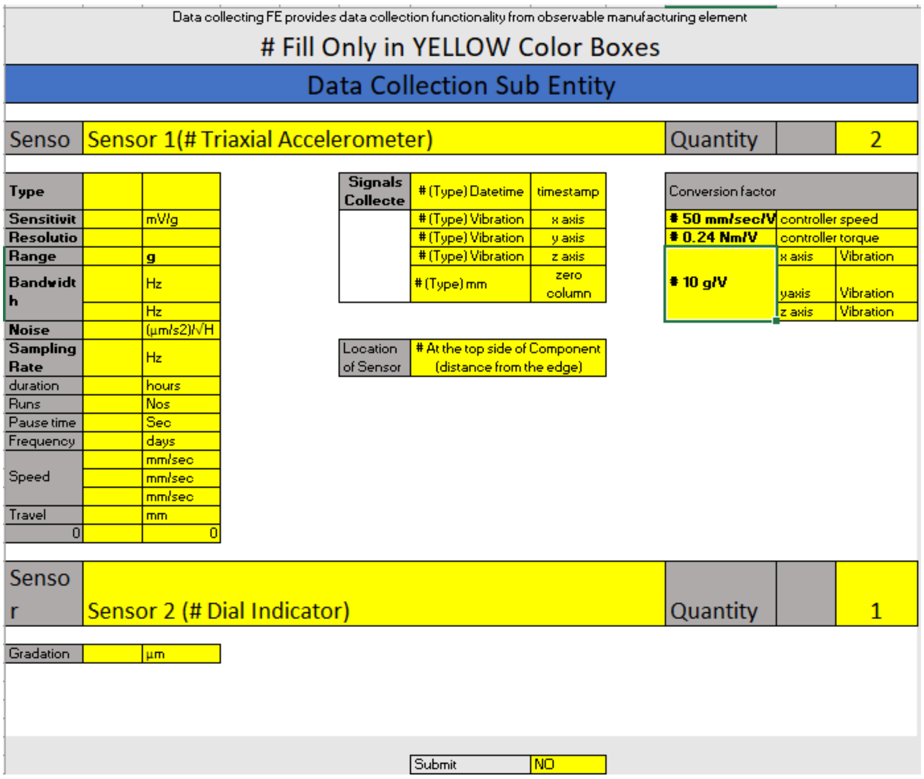
Figure 16 gives dynamic data pertaining to the operation related to the physical asset. As shown, the operational processes change with time, and the changes over time can also significantly affect the key process parameters. These changes have a direct effect on the behavior and overall performance of the physical asset. Thus, it is crucial to keep capturing and documenting these dynamic changes so that they can facilitate correct analysis, ensure operational reliability, and improve the predictive functionality of the digital twin system.

Environment	During the Process	# Component Name		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Information to identify environment including time and location	# Combination of time, sensor ID and sensor value		
		# Combination of time and energy consumption (kWh)		
Characteristics	Classification of Environment	Temperature		# units
		Humidity		# units
		Illuminance		# units
Schedule	Working Schedule for environment	Periodic		# One time
		duration	3	hours
		Pause time	10	sec
		Frequency	3	days
Relationship	Static Relationship for environments and other manufacturing elements	# Room #2 should be kept at 20 °C while manufacturing is being performed		
Description	Additional information and explanation about the static information of process	# any other general information about environment		
Dynamic Information				
Attribute	**Description**	**Examples**		
Status	Status of the environment	Normal		
Location	Location information (geographical / relative location)	# May 14th, 2019 10 AM: temperature #2 is 25 °C in Room #3		
Report	Working report related to environment	# May 14th, 2019 9 AM: Room #2 reports alarm of high temperature that the temperature #2 is 30 °C.		
Relationship	Dynamic Relationship for environment and other manufacturing elements	# May 14th, 2019 10 AM: Person #3 turned on the Facility #3(air conditioner) to lower Temperature #2 to 20 °C.		
Description	Additional information and explanation about the dynamic information of environment	# dynamic information of environment changing during manufacturing processes		
	Submit	NO		

Figure 17: Both Static and Dynamic information of the environment where the physical asset is located

The environment where the physical asset is located can also affect the performance of the physical asset. Hence, the basic detail of the environment needs to be captured.

Referring to Figure 18, there is a need to determine the types of sensors employed in collecting data and the type of data they provide. The data sheets on the sensors are important in assessing the quality of sensors and the validity of data obtained. Most important parameters like sampling rate, sensitivity, resolution, and data conversion factors are important since they have a direct influence on the reliability and accuracy of the measurements obtained.



Data collecting FE provides data collection functionality from observable manufacturing element

Fill Only in YELLOW Color Boxes

Data Collection Sub Entity

Senso	Sensor 1(# Triaxial Accelerometer)	Quantity		2

Type		
Sensitivit		mV/g
Resolutio		
Range		g
Bandwidth		Hz
		Hz
Noise		(µm/s2)/√H
Sampling Rate		Hz
duration		hours
Runs		Nos
Pause time		Sec
Frequency		days
Speed		mm/sec
		mm/sec
		mm/sec
Travel		mm
0		0

Signals Collecte	# (Type) Datetime	timestamp
	# (Type) Vibration	x axis
	# (Type) Vibration	y axis
	# (Type) Vibration	z axis
	# (Type) mm	zero column

Location of Sensor	# At the top side of Component (distance from the edge)

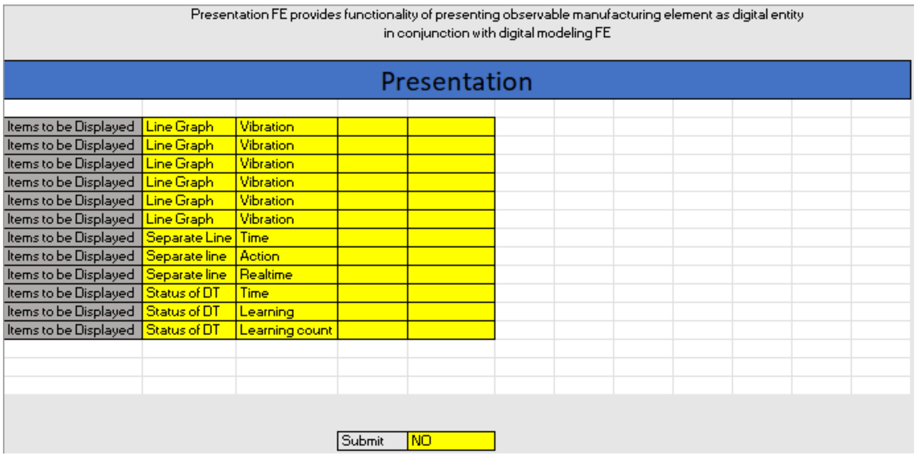
Conversion factor		
# 50 mm/sec/V	controller speed	
# 0.24 Nm/V	controller torque	
# 10 g/V	x axis	Vibration
	yaxis	Vibration
	z axis	Vibration

Senso r	Sensor 2 (# Dial Indicator)	Quantity		1

Gradation		µm

Submit	NO

Figure 18: Details need to be filled in by the Data Acquisition Engineer about the types of sensors and the type of data retrieved



Presentation FE provides functionality of presenting observable manufacturing element as digital entity in conjunction with digital modeling FE

Presentation

Items to be Displayed	Line Graph	Vibration
Items to be Displayed	Line Graph	Vibration
Items to be Displayed	Line Graph	Vibration
Items to be Displayed	Line Graph	Vibration
Items to be Displayed	Line Graph	Vibration
Items to be Displayed	Line Graph	Vibration
Items to be Displayed	Separate Line	Time
Items to be Displayed	Separate line	Action
Items to be Displayed	Separate line	Realtime
Items to be Displayed	Status of DT	Time
Items to be Displayed	Status of DT	Learning
Items to be Displayed	Status of DT	Learning count

Submit	NO

Figure 19: Details to be filled in by the product manager

On the presentation sheet in figure 19, which can be thought of as a dashboard, it refers to the nature of information to be displayed, the corresponding plots, and parameters. The choice of these should go in sync with the goals discussed previously by the product manager. The data presented in the dashboard is filled based on the objectives previously discussed.

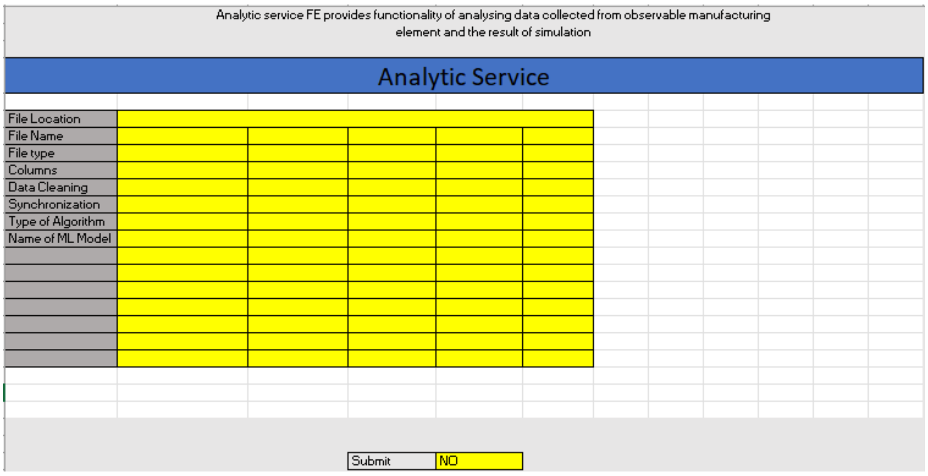


Figure 20: Details need to be filled in by the data scientist as per the objectives provided by the product manager

The Analytical Service Sheet in figure 20 is the center of the digital tool, where all the analytical processes are carried out. The sheet is required to have information on the data location, the type of information in the data files, data cleaning process steps, synchronization on timestamps, and the choice of suitable algorithms specific to desired objectives. It is up to the data scientist to fill this sheet with the required information. The outcomes derived from such analysis steps are then displayed on the dashboard so that they adhere to the objectives.

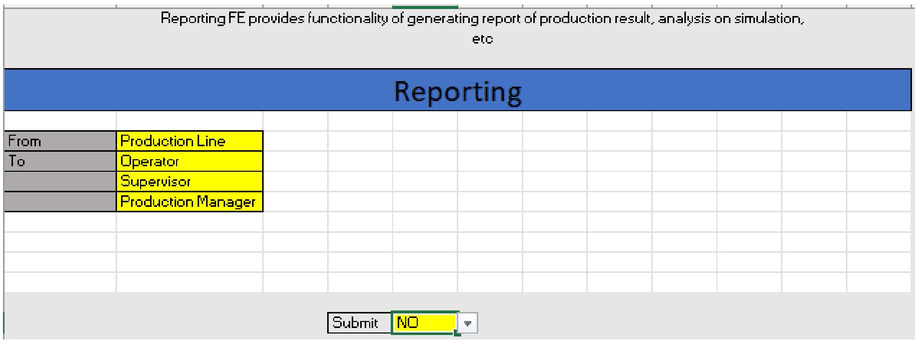


Figure 21: Details need to be filled by the product manager to define the user roles to display specific information to them on the dashboards

The Reporting Sheet in figure 21 holds crucial information that is uniquely designed for the user roles set by the product manager. For example, in a manufacturing environment, when a maintenance operator inputs information through the system, this input may have to be escalated to the higher authorities. Such information flows and user roles responsible for viewing and acting on the data included in the dashboards are defined in the Reporting Sheet.

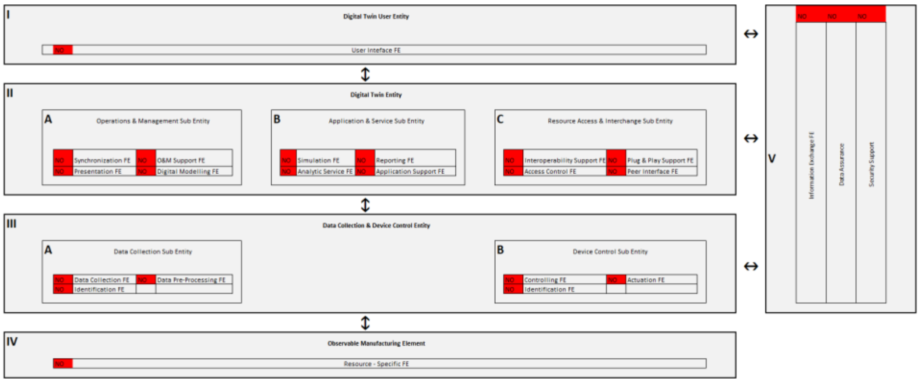


Figure 22: The basic overview of the DT setup tool at the end resembles the ISO 23247 architecture

From the above figure, the digital twin setup tool we have implemented follows the ISO 23247 reference architecture very closely (Figure 2). In the diagram, the red-colored boxes signify that the corresponding functional entity is incomplete or awaiting input. After the appropriate domain experts complete and submit the corresponding sheets, the color turns green from red, which indicates that the respective functional entity has been finalized with proper data. It summarizes what has been done and what still needs to be done. Users can easily determine from this data who needs to give the rest of the data and by which relevant functional entities, thereby helping in the development of DT. The full structure and functionality of the digital twin setup tool will be illustrated through a series of case studies discussed in the subsequent sections of this study. This graphical illustration also aids in monitoring the completion level of each functional entity and helps identify the remaining data needed for the development of the DT.

Chapter 3 – Case Study 1 - Creality Ender 3 Neo 3D Printer

This chapter provides a comprehensive review of the datasets utilized in the case study for DT implementation, along with the experimentation and results.

3.1 Creality Ender 3 Neo 3D Printer Dataset

The first dataset employed in this research consists of timestamped position data from a Creality Ender 3 Neo 3D printer, capturing the nozzle head movement along the x, y, and z directions. The experimental setup involved printing a square shell component with dual-layer geometry, featuring an inner shell of 8 mm × 8 mm dimensions and an outer shell of 10 mm × 10 mm dimensions. The analysis was conducted under the assumption of constant nozzle head acceleration throughout the entire printing process.

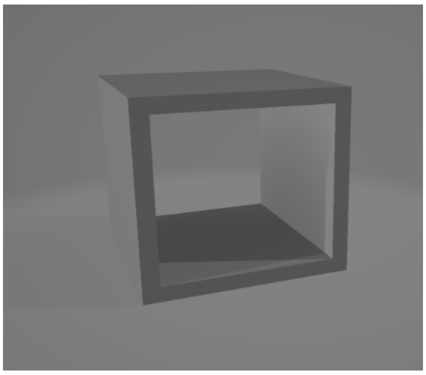


Figure 23: CAD model of a square shell

The experimental parameters were systematically varied to capture the effect of different operational conditions on the printing process. Feed Factor percentages were set at 50%, 75%, and 100%, while Layer Height was varied between 0.1 mm, 0.2 mm, and 0.3 mm. Belt Tension was adjusted across three levels (1, 2, and 3) to evaluate its impact on positioning accuracy and print quality.

Table 2: Machine parameters table

Parameters	**Levels**
Feed Factor (%)	50, 75, ***100***
Layer Height (mm)	0.1, ***0.2***, 0.3
Belt Tension	***1***, 2, 3

Data acquisition was accomplished through optical encoders interfaced with an Arduino board, enabling real-time capture of nozzle position data during the printing process. The integration methodology involved generating reference data from CAD files, which were converted into G-code format containing nozzle position coordinates, feed rates, extrusion parameters, and temperature profiles. A specialized Python script was developed to extract temporal data from G-code files, creating comprehensive CSV datasets that served as the foundation for machine learning algorithm development and Digital Twin modeling.

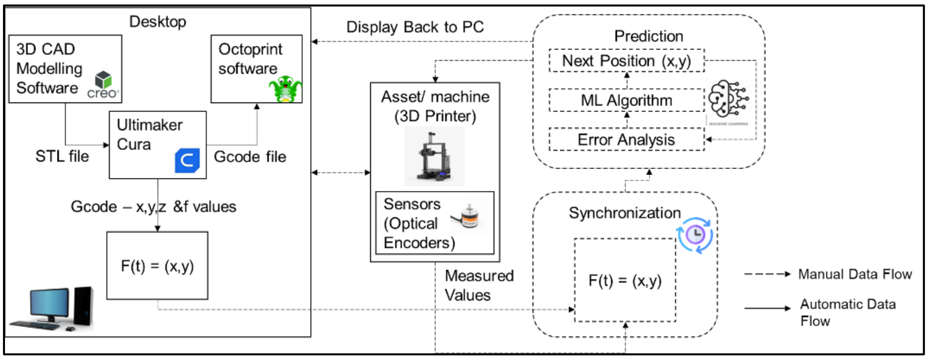


Figure 24: Flow diagram of integrating the predicted values into the actual machine (Creality Ender-3 Neo)

From the above figure, the left block explains to us how the reference data is generated from the CAD file to x, y, &z values of the nozzle position of the 3D printer. The g-code file contains the nozzle position, feed, extrusion rate, and temperature of the nozzle, etc. A Python script is written in such a way that the values from the g-code files are extracted along with the timestamp and stored in a CSV file. Then, in the middle, there are sensors, optical encoders, that capture the measured values of the position of the nozzle in the 3D printer along with the timestamp and store them separately in a CSV file. These two CSV files act as the source for the ML algorithms to predict the values as per the objectives.

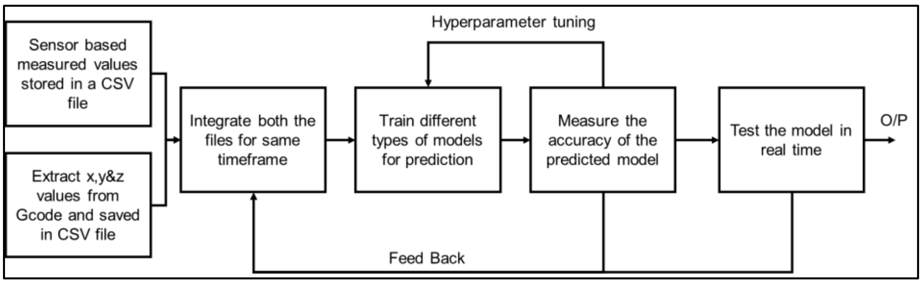


Figure 25: The overall approach to predicting the values from the Creality Ender-3 Neo 3D printer dataset

3.2 Experimentation and Results

This dataset was used only for analytical purposes. In the development of the digital twin, data analytics has been at the heart of it. So, predicting the values using the right algorithm is one of the complex tasks. Two algorithms were used for predicting values. They are Auto Regressive Moving Average (ARMA) and Kalman Filter. These algorithms were selected based on their nature of flexibility in time series data and computational load on a real-time basis. Let's discuss each of the algorithms one by one and their usage on this current dataset.

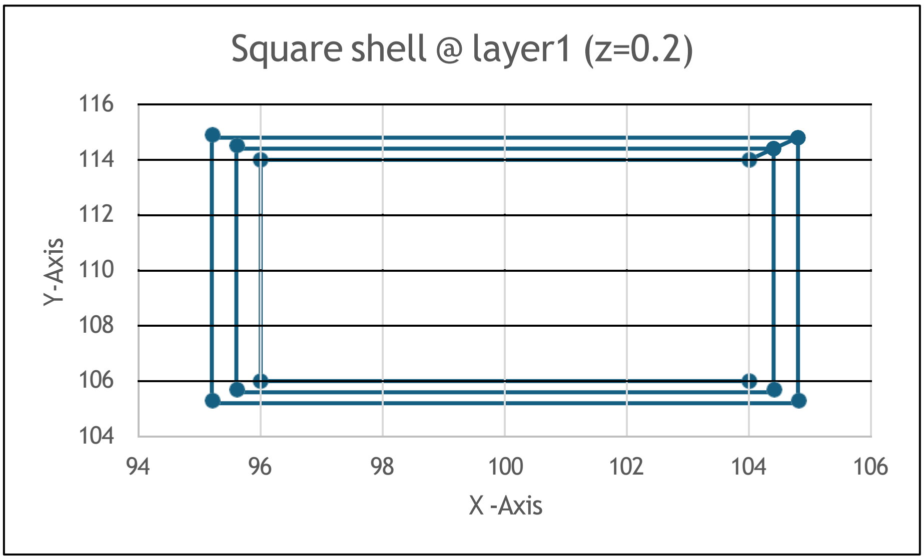


Figure 26: Line plot of square shell, the 3D printed product based on g-code data (values are in mm)

The starting point for toolpath generation was taken from the G-code file of the first layer (Z = 0.2 mm) of the printed part. The optimum path is shown in Figure 11, which shows the command path of the print head in the X-Y plane. It is an approximate rectangular shell with well-defined corners and straight linear sides. This course is the ground truth or reference path from which all later measured and predicted movements are calibrated.

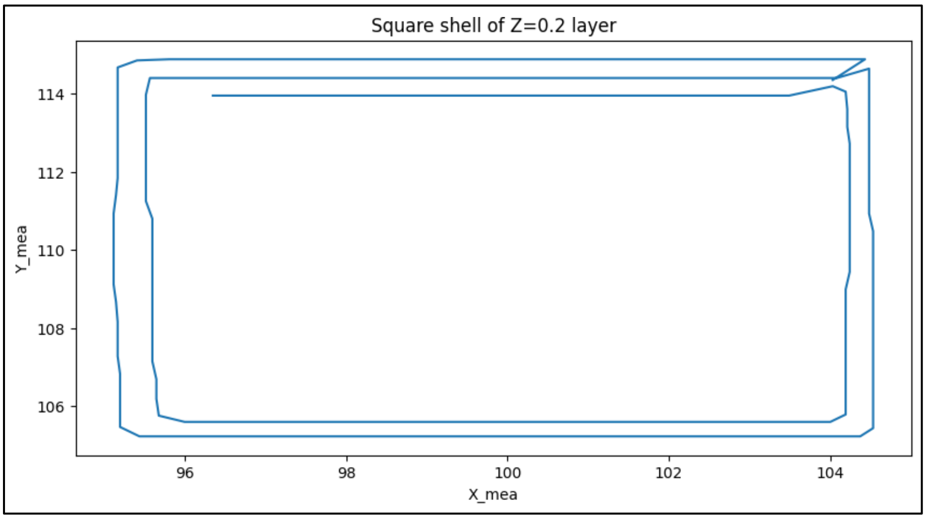


Figure 27: Line plot of square shell, the 3D printed product based on sensor data (values are in mm)

The true toolhead motion was captured using sensor-annotated feedback and graphed to see the physical excursions from the optimal G-code path. Figure 12 shows the measured tool path. The overall geometry of the square shell is maintained, a sign that the machine traced the planned path with good faithfulness. Still, some deviations from the optimal route are evident. Namely:

- The corners of the measured shell have minor rounding, as opposed to sharp corners on the G-code.
- The lines, although predominantly straight, have minor curvatures and irregularities.

Such deviations can be caused by mechanical backlash, structural vibration, or control errors inherent in the motion system of the machine. However, the measured data does not exceed acceptable limits, and the closeness of the data to the desired path assures satisfactory system performance.

3.2.1 ARMA Algorithm

To predict the future position of the toolhead, an Autoregressive Moving Average (ARMA) model was used to the measured trajectory data. The goal was to investigate if ARMA was able to learn the motion pattern and make useful predictions for the subsequent steps of tool movement.

Figure 13 shows the results of the predictions. The blue line indicates the measured historical values, and the orange line indicates the predicted future values as given by the ARMA model. The following observations can be made:

- The predictions are far from the trajectory range of observation. While the measured values hover within the X-range of about 95 to 105, the predictions are found in a far-off range (about 180 to 200).
- There is a total disconnection between the historic movement and the forecast path, which shows that the ARMA model could not replicate the spatial dependencies or system dynamics.

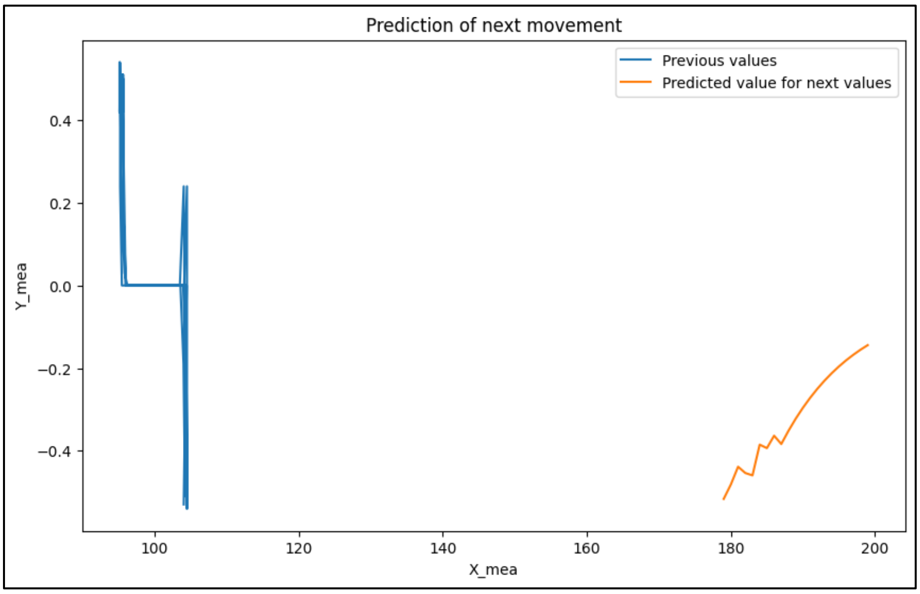


Figure 28: Line plot of square shell, the 3D printed product after applying ARMA algorithm (values are in mm)

This divergence implies that the ARMA model is not appropriate for such multi-dimensional time-series data, where both spatial and temporal features have to be addressed in concert.

The results indicate that the physical execution of the G-code is reasonably accurate, but the ARMA model does not predict the next sequence of movement steps accurately. The high standard deviation of predicted values indicates either bad model training, bad data preprocessing, or the limitations of the ARMA method in this area of application.

3.2.2 Kalman Filter

In this section, the Kalman filter algorithm is examined to improve the quality of measured data during the 3D printing process. The objective is to reduce sensor reading noise and improve the precision of the movement path of the nozzle in comparison to the G-code path. Also, the ability of the Kalman filter is tested to project future positions, which has potential uses in digital twin models and real-time process monitoring.

Impact of Time Step on Performance of Kalman Filter

Two different configurations of the Kalman filter were run, with time steps (dt) at 0.5 sec and 5.0 sec, respectively. These provide an opportunity to check the effect of updating frequency on the accuracy and responsiveness of trajectory estimation.

(a) Kalman Filter with dt = 0.5 sec

Figure 29 shows the estimated trajectory with the Kalman filter having a reduced time step of 0.5. The filtered trajectory (green) has an extremely high level of fidelity to the actual measured path (blue) and desired G-code path (orange). Measurement noise is greatly reduced by the filter and the important features of the trajectory are maintained. Corner transitions are well captured, though slight delays are noticed due to the recursiveness of the filter

Next, let us assume the same example that we have discussed in the previous algorithm (ARMA) and pass the values through KF algorithm the below is the plot that we observe

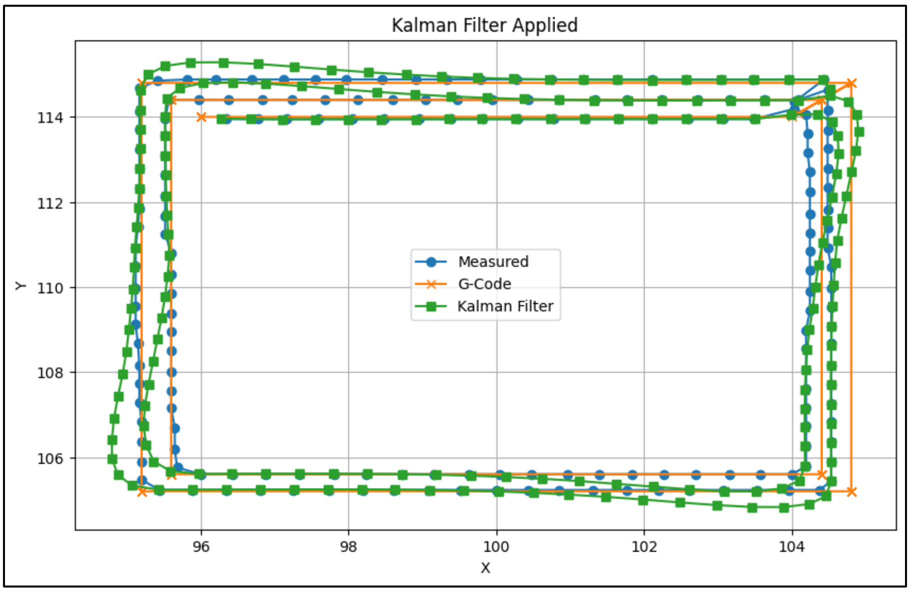


Figure 29: Line plot of square shell after applying the Kalman Filter algorithm (values are in mm) for dt = 0.5 sec

For a change in dt = 5.0 sec, the change in the path of the predicted values is plotted in the figure below.

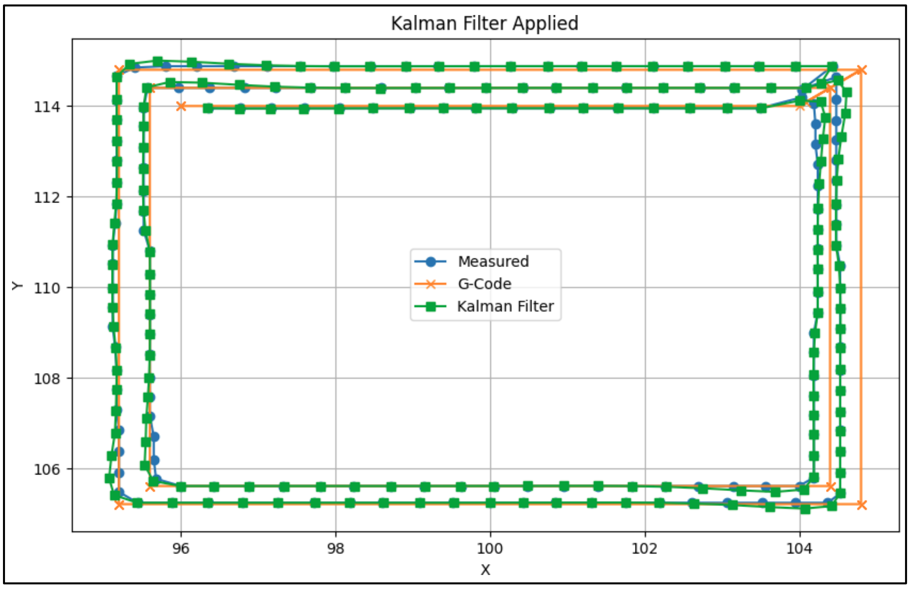


Figure 30: Line plot of square shell after applying the Kalman Filter algorithm (values are in mm) for dt = 5.0 sec

If we go deep into the specific side (left) of the square shell, then we can see the points that KF predicted.

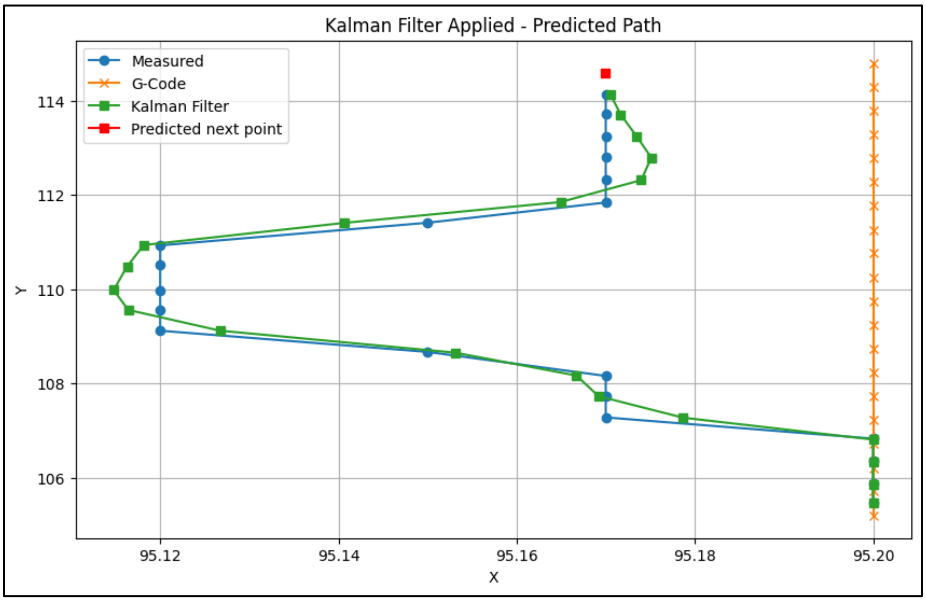


Figure 31: Line plot of left of the external square shell after applying the Kalman Filter algorithm (values are in mm) for dt = 5.0 sec

The results indicate that a smaller time step (dt = 0.5) improves tracking accuracy and is more appropriate for settings where frequent high-frequency updates are present. A large time step (dt = 5.0) helps filter noise in low-dynamic conditions but can be detrimental to precision during sudden directional changes. The Kalman filter efficiently produces smooth trajectories from noisy observations. The Kalman filter's prediction capability paves the way for real-time error detection and correction, anomaly identification, and predictive analysis.

These results favor incorporating Kalman filtering as a building block in smart manufacturing systems, particularly in condition monitoring, process optimization, and digital twin applications

Due to the limited data available in the dataset, the dataset was changed to include the complete lifecycle of the component (Ball Screw), which was already mentioned in Chapter 2.

Chapter 4 – Case Study 2 – Ball Screw

In this Chapter we will be discussing about the implementation of the digital twin setup tool which was developed and build the digital twin for Ball Screw component.

4.1 Ball Screw Dataset

The new dataset is taken from the "NIST Public Data Repository, Linear Axis Testbed at IMS Center – Run-to-Failure Experiment 01" repository.

A concrete slab that weighed about 1700 kg had the linear axis screwed onto it. The carriage is moved nominally parallel to the X-axis by a ball screw that revolves via a motor. For a total possible journey of 450 mm, the carriage is constrained to move nominally linearly along the guideway by four trucks with ball bearings making contact with two rails. The carriage is laden with 100 kg of steel weights to hasten the degrading process, which will occur during months of back-and-forth operation. Data is gathered using two triaxial accelerometers with a nominal sensitivity of 100 mV/g. In the IMU, the digital rate gyroscope has a half-power bandwidth of 0 to 200 Hz and a noise output of 35 (μrad/s)/~Hz, while the analogue accelerometer has a half-power point bandwidth of 0 to 300 Hz, nominal sensitivity of 2000 mV/g, and a noise output of 7 μg rms/~Hz. During axis degradation, information from these 12 inertial sensors is recorded in addition to controller data. With a data gathering strategy that mirrored real-life operation and monitoring, the new linear axis was run to failure (RTF). Data collection for ball screw health monitoring was carried out in two stages Phase I and Phase II.

4.1.1 Phase I Data Collection

A centered 220-mm-long stroke (movement between 110 and 330 mm relative to the zero position) was used to move the linear axis back and forth continuously, day and night, and this represents roughly half of the entire available trip. At 400 mm/s, the axis travels in both positive and negative directions. Every movement direction was followed by a one-second break. The regular operation of a linear axis in industry was symbolized by its continuous movement. To prevent undesired transitory behavior, data collecting starts after a notional 2-hour first warmup operation period. At a sample rate of 10 kHz, 10 s of data were gathered every 30 minutes throughout this initial phase. Data gathering for online incipient defect detection is represented by this collection mode.

4.1.2 Phase II Data Collection

The second phase of data collecting temporarily interrupts the first phase every three or four days. The axis is moved back and forth with a full stroke of 450 mm in this second phase. The axis moves back and forth at three different speeds during each run: slowly (20 mm/s), moderately (100 mm/s), and quickly (500 mm/s). This second phase consists of 90 runs. Data collection takes place over three hours, partly because of the 10-second rest time between each of these moves. For every run, IMU data are obtained at a sampling rate of roughly 1000 Hz for the gyroscope and 1613 Hz for the triaxial accelerometer.

According to the manufacturer's instructions, this two-phase experimental data gathering process was repeated until the ball screw reached an ultimate failure point larger than 10 μm. The ball screw was not lubricated at any point during the trial. Days 0 through 38, 116 through 255, and 377 through 574 were all included in the experiment's duration. The ball screw accrued 8693 operating hours over this period. Extenuating factors led to the trial being halted for days 38 through 116 and days 255 through 377. An extra step is occasionally conducted to get backlash measurements that monitor the axis' deterioration over time when transitioning from the first to the second phase. Sub gradation measures were determined by eye using a dial indicator with a gradation of 12.7 μm.

The dial indicator's lever is orientated so that its tip nearly touches the steel weights on the ball screw carriage and is programmed to rotate in the XY plane. After the dial indicator is in place, it is attached to the testbed base using a magnetic base. After measuring the dial indicators, the ball screw is instructed to travel successive fixed distances at intervals of 1 μm. Human observation is then used to identify the position of the lever's first contact with the dial indicator. The process is then carried out repeatedly in both positive and negative directions, with the exception that the position of the last touch is ascertained for the negative direction.

Table 3: Experiment Timeline of the Ball Screw

Day	Ball Screw Operational Hours	Event
0	0	Start
38	855.5	Pause
116	855.5	Resume
255	4033	Pause
377	4033	Resume
574	8693	End

In the above five paragraphs, the data collection method was explained, and the entire experimental setup was presented in the literature to understand the dataset completely.

4.2 Experimentation and Results

Now, for this dataset, I have performed PCA T^2 Analysis, and the results are shown below. But before that, let us understand what PCA T^2 is and how it can be used for this dataset.

In the figure 32, the plot shows the PCA T-squared (T^2) statistic applied to your ball screw dataset over 1st week and similarly in figure 33, it was applied over 89 weeks. On the X-axis, it is labelled as "Observation across

89 weeks", which represents all the individual data points collected over time.

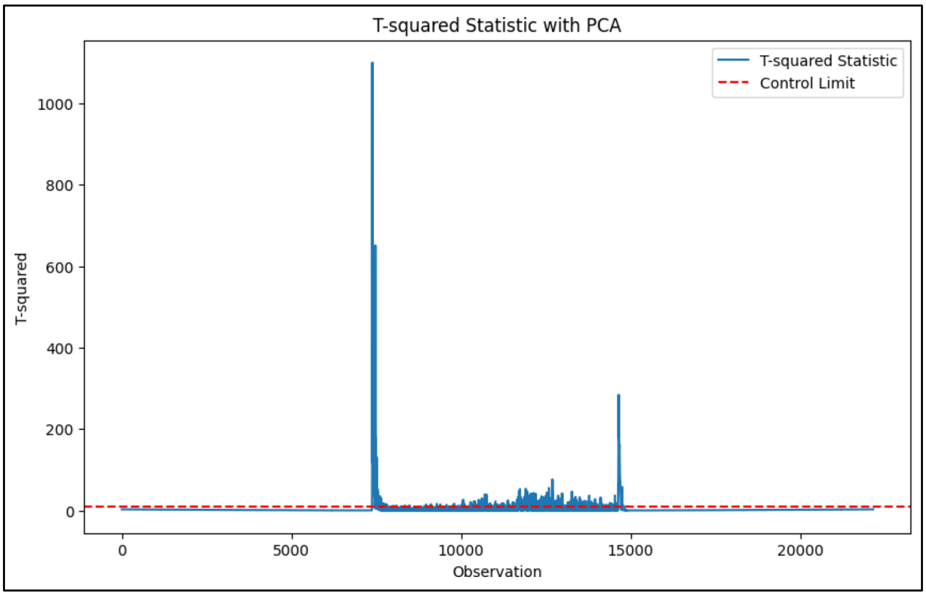


Figure 32: PCA T^2 statistic for 1st week data

This is a flattened view where all weeks' observations are laid out one after another. On the other hand, the Y-axis is labeled as "T-squared", which represents the T^2 statistic value for each observation. Higher values indicate greater deviation from the PCA model's normal behavior. Red Dashed Line, which is the Control Limit.

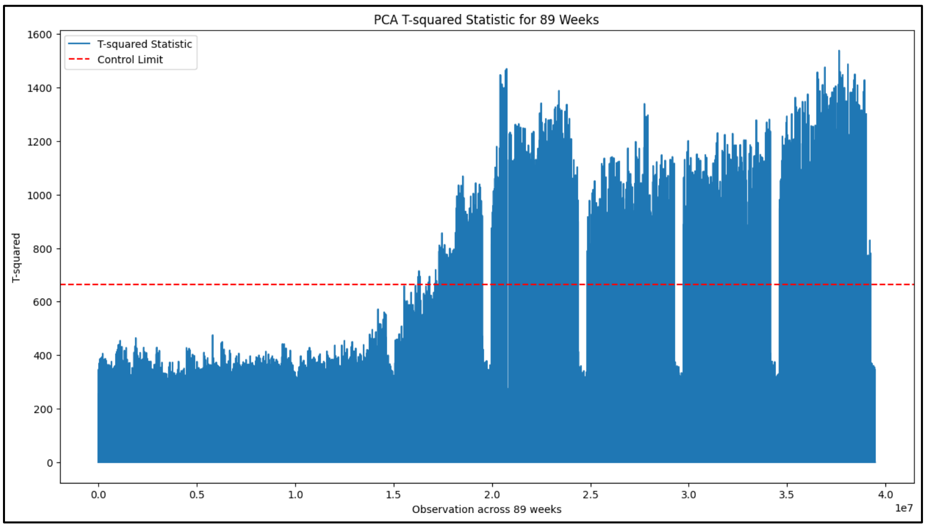


Figure 33: PCA T^2 statistic for all 89 Weeks of data

This is the T^2 threshold based on a confidence level (95%). Points above this line is considered anomalies, faults, or unusual behavior in the ball screw system.

What the plot tells us is that in the Early phase (left side), the T^2 values are low and stable, indicating normal operation. Middle to later phase (center to right), the sudden spikes and sustained high values indicate that T^2 values frequently cross the control limit. This likely suggests degradation, wear, or emerging faults in the ball screw system. Periodic dips to zero tell us that these gaps indicate missing or dropped data, downtime or inactive monitoring, and reset or maintenance events. Thus, a clear trend of increasing deviation, especially after the halfway mark. This is a strong indicator that the ball screw is experiencing progressive degradation. The PCA T^2 metric is helping us identify when and where that deviation starts and grows, i.e., at 30 weeks.

To evaluate the performance of various machine learning algorithms on the ball screw dataset, four prominent regression models were implemented: Random Forest Regressor, Support Vector Regression (SVR), Extreme Gradient Boosting (XGBoost), and Multi-Layer Perceptron (MLP) Regressor. The models were assessed based on three key criteria:

1. Prediction Accuracy, measured by Mean Absolute Error (MAE),
2. Computational Efficiency, measured by training time on CPU (without GPU),
3. Model-specific Insights, derived from behavior and tuning requirements.

The results are summarized in Table 4 and discussed in detail.

Table 4: Performance of various machine learning algorithms on the ball screw dataset

Model Name	**Mean Absolute Error (MAE)**	**Insights**	**Computational Time (Without GPU)**
Random Forest	1.33075	Lowest Error among all Four models	9.2 min
Support Vector Regression	1.92968	Highest Error because it is sensitive to Hyperparameter Tuning	93.5 min
XGBoost	1.53233	This approach is effective in capturing Non-Linear Relationships – also requires HT	18.0 sec
MLP Regressor	1.68122	This model requires additional layers to learn	1.5 min

Among the four models evaluated, the Random Forest Regressor emerged as the most reliable choice, offering the lowest prediction error and robust performance even without extensive tuning. While XGBoost demonstrated impressive computational efficiency and acceptable accuracy, its dependence on tuning may limit plug-and-play applicability. SVR underperformed in both accuracy and computational time, indicating it may not be suitable for large-scale or real-time applications in ball screw condition monitoring. The MLP Regressor showed promise but would benefit from further exploration of deeper architectures or GPU-accelerated training.

This comparative analysis provides valuable insight into the trade-offs between model accuracy and computational efficiency, guiding the selection of appropriate models for predictive maintenance systems in precision mechanical components like ball screws.

Now, if we apply the developed Digital twin setup tool to this case study 2, Ball Screw. The figures were displayed accordingly in the next pages. But before that mapping of the entire physical setup was done for this case study and is shown in the figure below.

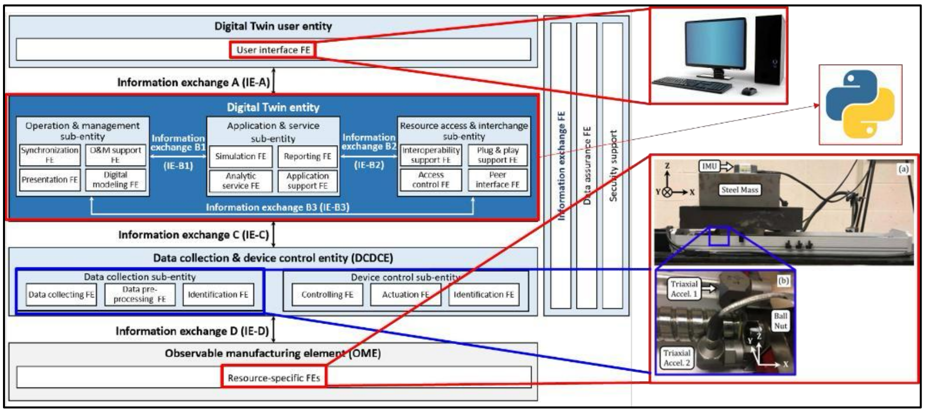
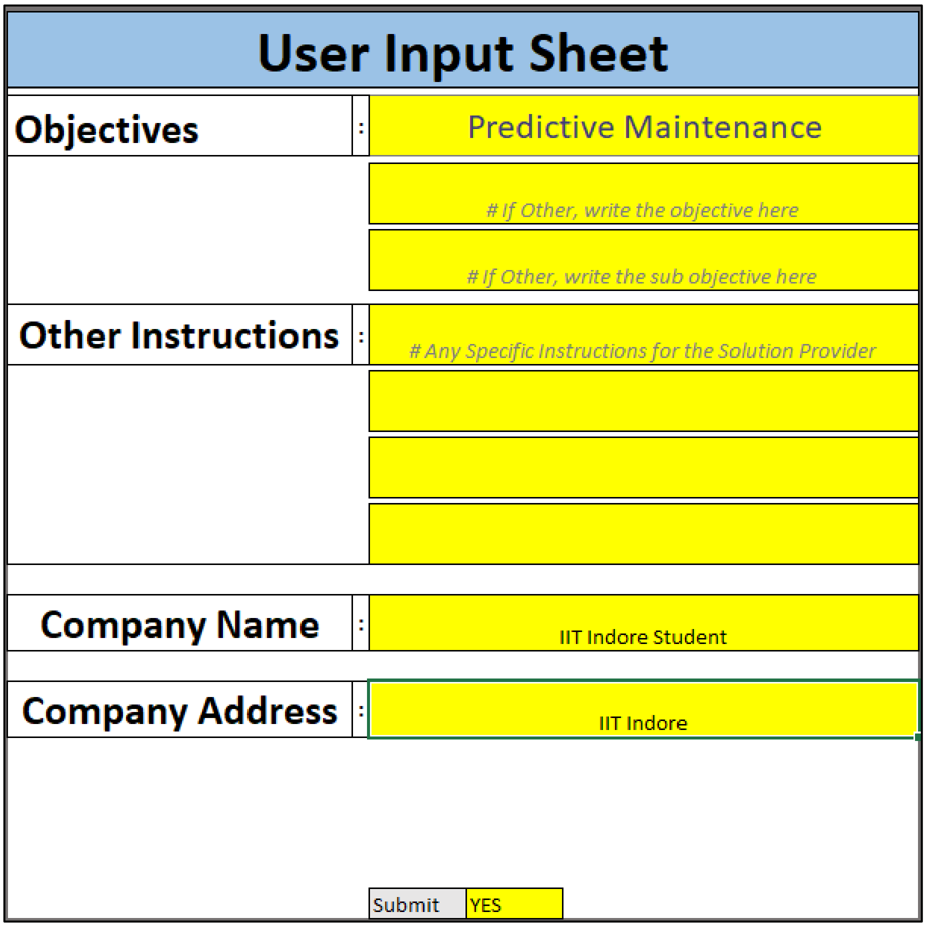


Figure 34: Mapping of the physical assets (Ball screw) to the ISO 23247 architecture



User Input Sheet		
Objectives	:	Predictive Maintenance
		# If Other, write the objective here
		# If Other, write the sub objective here
Other Instructions	:	*# Any Specific Instructions for the Solution Provider*
Company Name	:	IIT Indore Student
Company Address	:	IIT Indore
	Submit	YES

Figure 35: Cover Page in the Excel file to be filled in by the Product Manager

In the above figure, the basic details of the company (user) and its address are captured, along with its objectives. This helps us identify common component digital twins, which can be used as a template in the future when developing a digital twin for a similar component.

Observable manufacturing element shall be monitored and sensed, and may be actuated and controlled by data collection and device control entity. It includes personnel, equipment, material, process, etc

Fill Only in YELLOW Color Boxes

Observable Manufacturing Element (OME)

Equipment	**Ball Screw**	**Milling**		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Information to identify equipment	Model No	:	NA
		Part No	:	NA
		serial number	:	NA
		Dimensions	:	NA
		Material	:	stainless steel
		Price	:	NA
		Rating	:	NA
		Is the equipment SMART? If YES mention details	:	NO
		Is Warranty available?	:	NO
		Supplier Details	:	NA
		Lead Time	:	NA
		Add any extra Identification Parameters (if required)	:	NA
Characteristics	Classification of Equipment	Type of Operation		Milling
		Any Sub Operation		NA
Schedule	Working Schedule for Equipment	Working schedule		24/7
		Maintainance schedule		NO
Relationship	Static Relationship for equipment and other manufacturing elements	Milling Machine operates with Cast Iron Block		
		NA		
		NA		
Description	Additional information and explanation about the static information of equipment	NA		

Figure 36: Static details of the Ball Screw

Dynamic Information					
Attribute	**Description**		**Examples**		
Status	Status of the equipment		Off		
			Breakdown		
		Performance	Products (output)	NA	
			Energy Usage	NA	kWh
			Output	NA	W
			Temperature	YES	C
			Noise	NA	dB
			Pitch	10	mm
			Vibration	YES	mm
			Backlash	YES	µm
			Torque	YES	Nm
			Extra Load (kgs)	100	kgs
			Pressure	NA	Mpa
Location	Location information (geographical / relative location)		Ball Screw is located near the Lead Screw of Milling Machine		
			NA		
			NA		
Report	Working report related to Equipment		Due to unforeseen circumstances the machine stopped for 200 days over 574 days		
			NA		
Relationship	Dynamic Relationship for equipment and other manufacturing elements		NA		
Description	Additional information and explanation about the dynamic information of equipment		NA		

Figure 37: Dynamic details of the Ball Screw

Process	Type of Operation	Ball Screw		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Information to identify Process	Process Identifier		Milling
Characteristics	Classification of Equipment	Production		YES
		Maintenance		NO
		Quality Test		NO
		Inventory		NO
		Milling		YES
		Drilling		NO
		Additive		NO
Schedule	Working Schedule for Process	Periodic		One time
		duration	3	hours
		Runs	90	Nos
		Pause time	10	Sec
		Frequency	3	days
		Speed	20	mm/sec
			100	mm/sec
			500	mm/sec
		Travel	450	mm
Relationship	Static Relationship for process and other manufacturing elements	Ball Screw is operated with extra load of 100 kgs		
Description	Additional information and explanation about the static information of process	NA		
Dynamic Information				
Attribute	**Description**	**Examples**		
Status	Status of the Process	Planned		
		Completed		
		Stopped Abruptly		
Location	Location information (geographical / relative location)	NA		
Report	Working report related to process	NA		
Relationship	Dynamic Relationship for process and other manufacturing elements	NA		
Description	Additional information and explanation about the dynamic information of process	NA		

Figure 38: Details of the operation where Ball Screw is used

Environment	During the Process	Ball Screw		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Information to identify environment including time and location	NA		
		NA		
Characteristics	Classification of Environment	Temperature	NA	# units
		Humidity	NA	# units
		Illuminance	NA	# units
Schedule	Working Schedule for environment	Periodic		One time
		duration	3	hours
		Pause time	10	sec
		Frequency	3	days
Relationship	Static Relationship for environments and other manufacturing elements	NA		
Description	Additional information and explanation about the static information of process	NA		
Dynamic Information				
Attribute	**Description**	**Examples**		
Status	Status of the environment	Normal		
Location	Location information (geographical / relative location)	NA		
Report	Working report related to environment	NA		
Relationship	Dynamic Relationship for environment and other manufacturing elements	NA		
Description	Additional information and explanation about the dynamic information of environment	NA		
	Submit	YES		

Figure 39: Details of the environment of Ball Screw

Data collecting FE provides data collection functionality from observable manufacturing element

Fill Only in YELLOW Color Boxes

Data Collection Sub Entity

Location	D:\Linear axis test bed(Vibhor sir dataset)\IMU Data

Sensor	Triaxial Accelerometer	Quantity	2

Type	Analog	
Sensitivity	2000	mV/g
Resolution	N/A	
Range	±2	g
Bandwidth	0	Hz
	400	Hz
Noise	69	(µm/s2)/√Hz
Sampling Rate	1613	Hz
duration	3	hours
Runs	90	Nos
Pause time	10	Sec
Frequency	3	days
Speed	20	mm/sec
	100	mm/sec
	500	mm/sec
Travel	450	mm
0	0	0

Signals Collected	Datetime	timestamp
	Vibration	x axis
	Vibration	y axis
	Vibration	z axis
	length	zero column

Location of Sensor	At the top side of Component (distance from the edge)

Conversion factor		
50 mm/sec/V	controller speed	
0.24 Nm/V	controller torque	
10 g/V	x axis	Vibration
	yaxis	Vibration
	z axis	Vibration

Sensor	Dial Indicator	Quantity	1

Gradation	12.7	µm

Submit	YES

Figure 40: Details filled in by the Data Acquisition Engineer about the types of sensors used in Ball Screw

Presentation

Items to be Displayed	Line Graph	Vibration	x axis	time
Items to be Displayed	Line Graph	Vibration	x axis	week
Items to be Displayed	Line Graph	Vibration	y axis	time
Items to be Displayed	Line Graph	Vibration	y axis	week
Items to be Displayed	Line Graph	Vibration	z axis	time
Items to be Displayed	Line Graph	Vibration	z axis	week
Items to be Displayed	Separate Line	Time	RUL	hours
Items to be Displayed	Separate line	Action	Alert	Message
Items to be Displayed	Separate line	Realtime	Timestamp	date and time
Items to be Displayed	Status of DT	Time		hours
Items to be Displayed	Status of DT	Learning	Yes	No
Items to be Displayed	Status of DT	Learning count		Nos
		Submit	YES	

Figure 41: Details required for Ball Screw dashboard

Analytic Service					
File Location	D:\Linear axis test bed(Vibhor sir dataset)\IMU Data				
File Name	Accelerometer				
File type	txt				
Columns	timestamp	x-axis vibration	y-axis vibration	z-axis vibration	zero column
Data Cleaning	Yes	Yes	Yes	Yes	No
Synchronization	Yes	Yes	Yes	Yes	No
Type of Algorithm	Classification	Prediction			
Name of ML Model	Random Forest	Linear Regression			
	Logarithmic Regression	.			
	.	.			
	.	.			
	.	.			
	.	.			
	.	.			
	so on	so on			
		Submit	YES		

Figure 42: Details need to be filled in by the data scientist as per the objectives provided by the product manager

Similarly the other domain experts fills in the details based on the requirement for developing the digital twin. The basic overview of how the tool looks like is shown in the below figure.

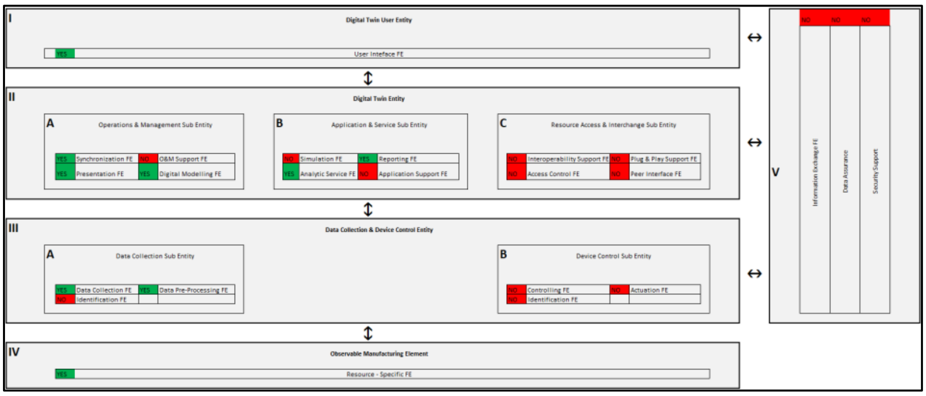


Figure 43: Overview of the Ball Screw DT setup tool

Overview of the Digital Twin Setup Tool after filling in the details by the respective domain experts looks like the above figure. The red color box indicates that the details were not filled in by the respective domain expert. The green color indicates that the information is captured and ready to use to develop the digital twin.

4.3 Digital Twin dashboard of Ball Screw

The DT setup tool, designed so far, covers all the necessary information needed to create an effective digital twin. A scripted approach is used to pull corresponding data from the DT setup tool and conduct the requisite analyses, which are plotted on the dashboard. The dashboard is interactive and enables users to enter data and track the status of the component along three important dimensions: historical performance, present condition, and future projections.

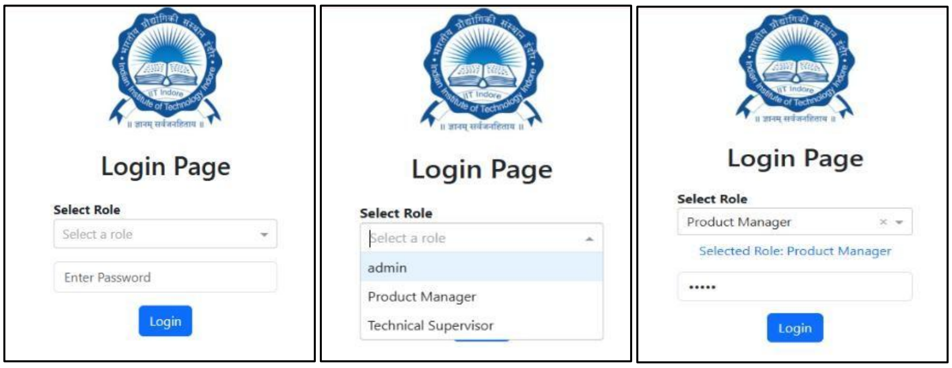


Figure 44 Dashboard displaying the login page

Once the code runs in the terminal, it redirects to the dashboard, asking the user to enter the role and password to investigate the stats of the digital twin.

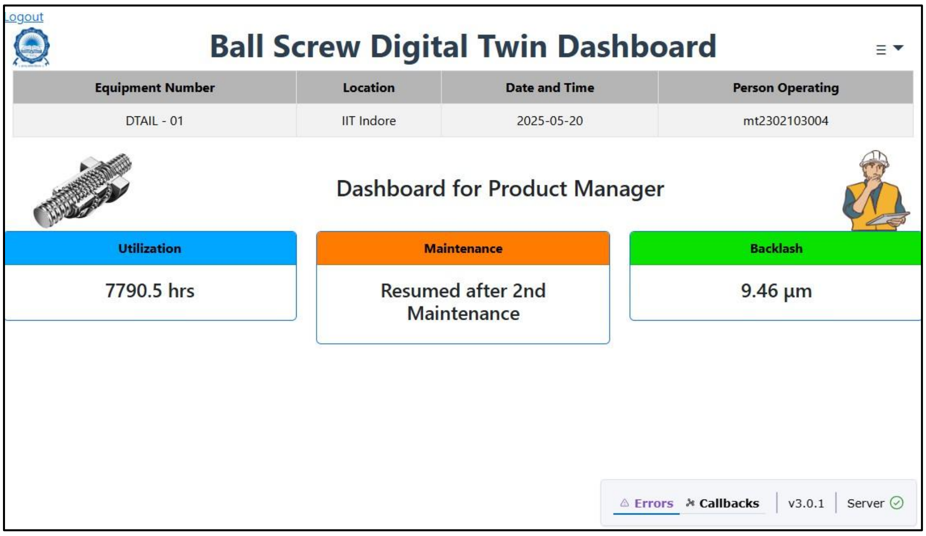


Figure 45 Dashboard displaying the stats for the Product Manager

After we have entered the respective role in the login page, it takes us to the dashboard, where it displays the basic stats of the product. In the

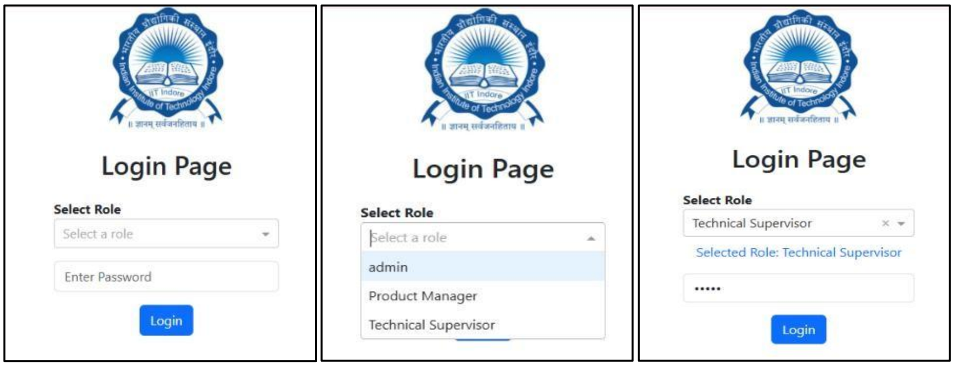


Figure 46: The dashboard displays the login page for another user

above figure, the chosen role was taken as a Product Manager, and hence only the basic details such as utilization, maintenance, and backlash have been displayed on it. With the use of this dashboard, the product manager will have the ability to see the entire statistics of the product and make decisions required to modify the process to improve efficiency and productivity.

After entering the another role by the user the dashboard for them would be similar to it but with some extra features added in it to visualize the digital twin. The assumed another role is Technical Supervisor, where they can visualize every details of the analysis how it was happened in the past, and currently what is happening and what will happen in the future.

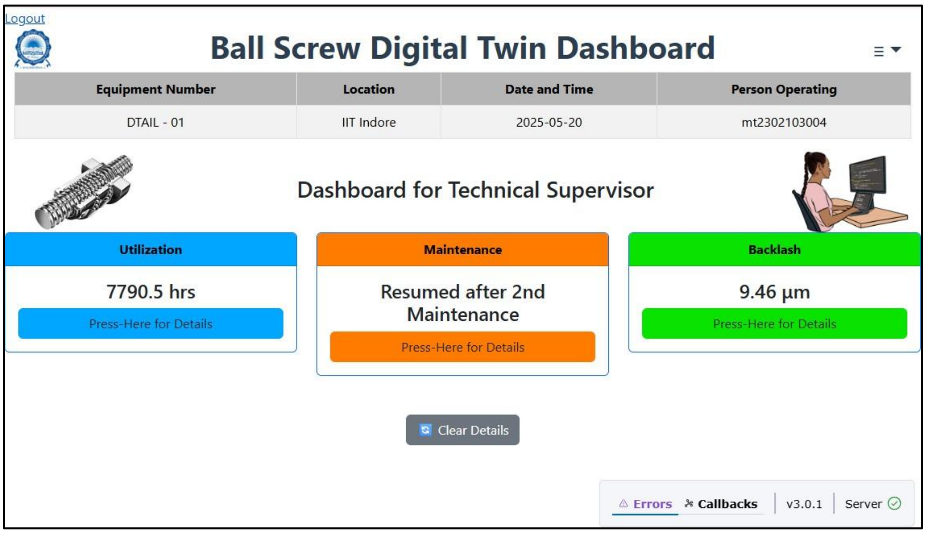


Figure 47 Dashboard displaying the stats for the Technical Supervisor

The technical supervisor can now look into the in-depth analysis of how the utilization, maintenance, and backlash parameters are changing. There is an option in each of the parameter containers to investigate the details deeply. If you click on the “Press Here for Details” button inside the parameter containers, then the analysis containers would be displayed in terms of past, present, and future.

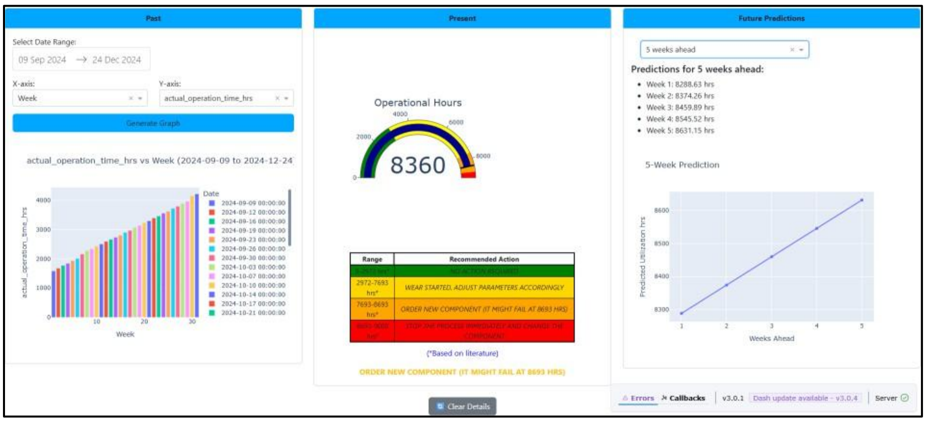


Figure 48 Dashboard displaying the analytical plots for the utilization parameter

We can observe from the above figure that at the left side of the dashboard, there is a past container where there is a date selector to choose the duration. Below, there are options to provide input to the x-axis, y-axis to plot the graphs. Depending on this user's selection, the bar plots are shown. From here, we can see what the trend is in that chosen time. Likewise, in the center of the dashboard, there is a current container that shows the status of the component and progress of the digital twin. In the above figure, there is a gauge plot showing the Operational Hours of the component, i.e., the time for which the product has been utilized up to the current date. In the same container below the gauge plot, there is a table indicating the recommended actions according to the usage of the product. In the right corner of the dashboard, there is a future container where we can observe the projected values and line plot according to the chosen weeks.

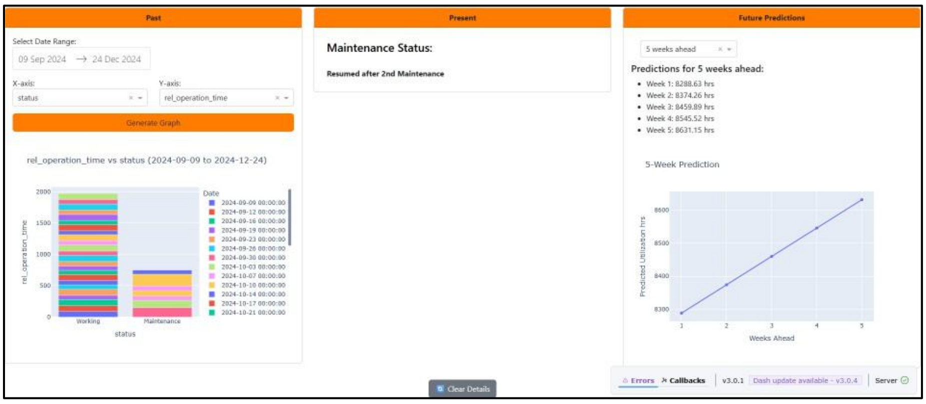


Figure 49 Dashboard displaying the analytical plots for the maintenance parameter

In the same way, in the maintenance parameter, on the left side of the dashboard, we have data of the product of how many hours it was operating and in maintenance. In the middle present container, we have the status of maintenance in the dashboard. In the future container the plot informs us when the product will fail and when to halt the process. On this basis, we can order the new part prior to its failure.

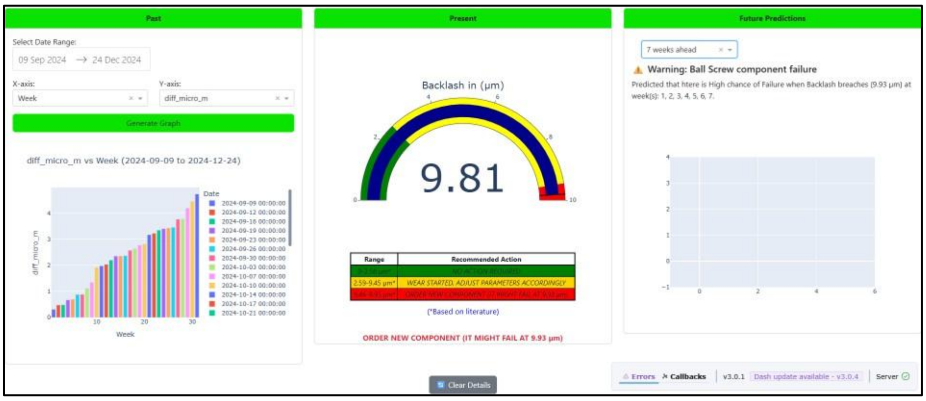


Figure 50 Dashboard displaying the analytical plots for the backlash parameter

Similarly, for the backlash parameter, all the containers will be identical, and the plots will vary depending on the parameter. Here, in the past container, the bar plot was between week and backlash. In a present container, the present backlash value is shown in the gauge plot, and a suggested action is also indicated below it. In the future container, depending on the chosen weeks, it shows any possibility of failure or future backlash values.

This chapter demonstrated the development and deployment of digital twin systems for two mechanical components: the Go 3D Artish 700 Printer and ball screw assembly. Utilization, production, and maintenance of the 3D printer were tracked using dashboards designed in a Past–Present–Future model to make predictive observations and operational efficiency. Similarly, the digital twin of the ball screw focused on utilization, maintenance tracking, and backlash monitoring to measure wear and performance degradation over time. Both installations illustrate the adaptability and versatility of digital twin technology for condition monitoring and predictive maintenance in different systems. These are examples of the potential of digital twins to facilitate transparency, reduce downtime, and support data-driven decision-making in state-of-the-art manufacturing environments

Chapter 5 – Case Study: Go 3D Artish 700

In this chapter, we shall discuss the practical application and implementation of the Digital Twin Setup Tool within the manufacturing context. This tool is essential in coordinating and connecting physical assets' static and dynamic information to their digital duplicates. The DT Setup Tool facilitates real-time analysis, condition monitoring, and predictive maintenance. This systematic approach facilitates enhanced visibility, traceability, and informed decision-making throughout different phases of the asset life cycle.

5.1 Go 3D Artish 700 3D Printer Dataset

This dataset has been created using web scraping, a technique where data displayed on a webpage is directly accessed using a Python script and then stored in a CSV file.

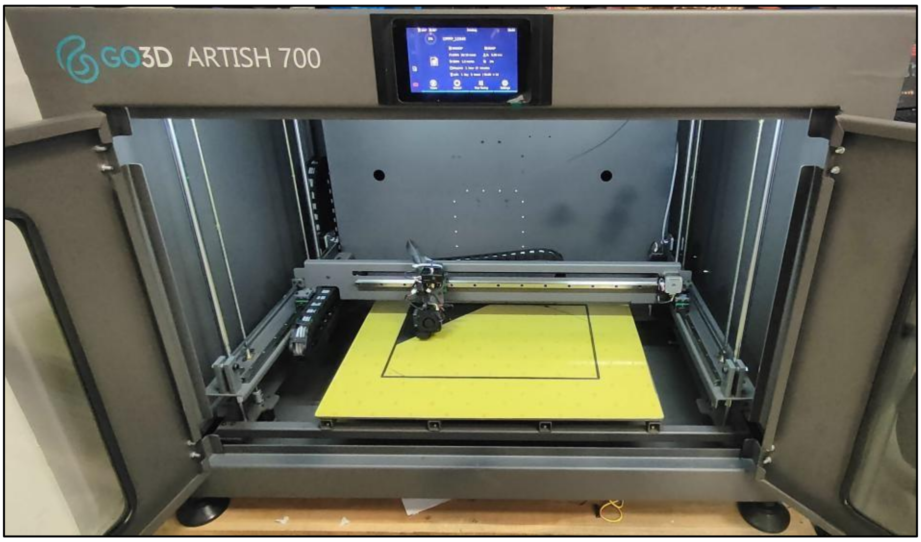


Figure 51: Go3D Artish 700 3D printer

The 3D printer incorporates a Revo Hemera XS extruder capable of 300°C temperature and 1.75 mm filament, 85.5 × 28.9 × 65.5 mm in size and weighing 256.25 g. The bed area is 700 x 500 mm with the capability of printing at a height of 500 mm. It runs on a 24V supply at 7000 rpm with a 1.8° step and is constructed from stainless steel and aluminum. GT2 timing belts (2 mm pitch, 153 g, rubber-fiber composite) drive the cast iron slider on the X and Y axes to the motion system. Yearly maintenance of the extruder, semi-annual gear checks, and yearly timing belt checks for stretching and sliders every 3–4 months are planned. The mechanism is additive in nature, runs constantly at a speed of ~60 mm/s, and at ambient temperatures of 25–27°C, with no routine breaks or halts.

5.2 Experimentation and Results

Here, different domain expert roles were assumed and filled out the respective sheets based on the data available, whether acquired through sensors or from literature.

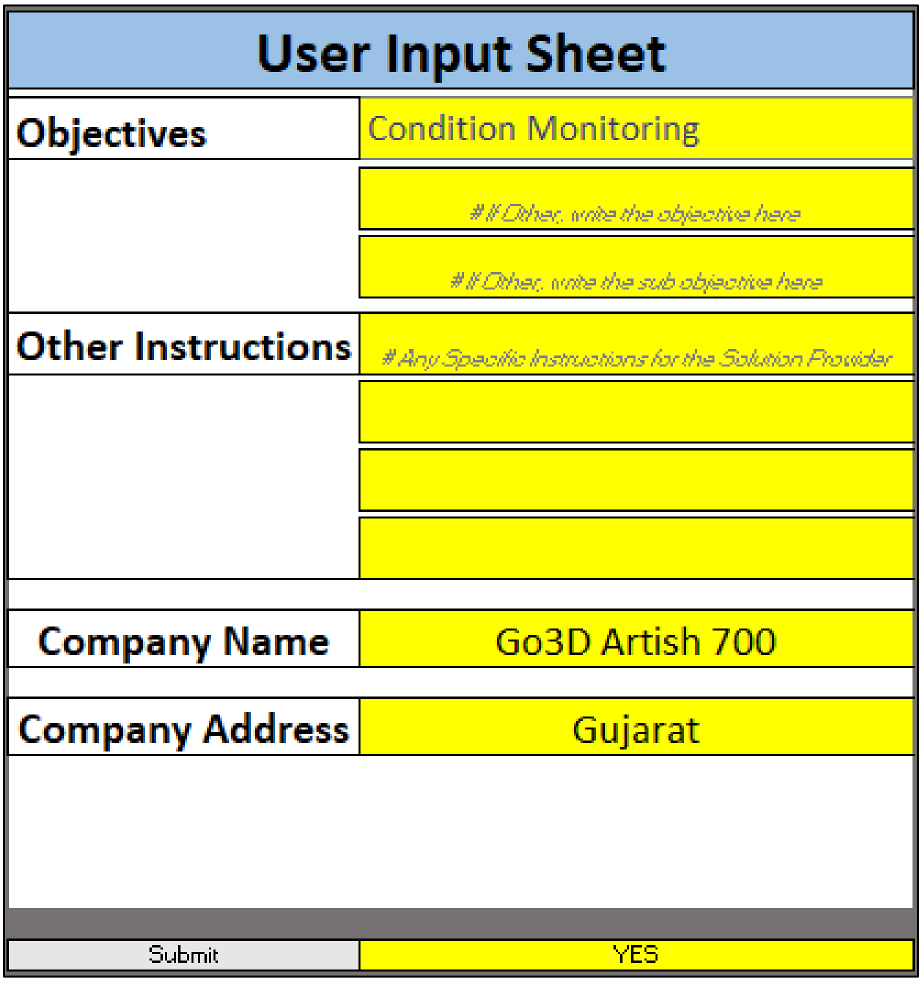


Figure 52: Input sheet of Go3D Artish 700 filled by Product Manager

For the 3d printer, the objective selected was condition monitoring, and the details of the company were filled as per the manufacturer of the 3d printer.

Component	Nozzle	3D Printer		
Static Information for the component				
Attribute	**Description**	**Examples**		
Identification	Information to identify component	Model No	:	E3D Revo Nozzle
		Serial number	:	RC-NOZZLE-0600-AS-SPK
		Material	:	Brass
		Sock Colour	:	Blue
		Dimensions (Design)	:	"C:\Users\gtman\OneDrive - IIT Indore\Digital
		Nozzle Dia	:	0.6mm
		Max Temperature	:	300
		Input Filament Diameter	:	1.75mm
		Types of Filaments can be used	:	PETG,PLA,ABS/ASA,TPU92A,TPU85A,TPU75A,XTCF20,PACF
		Price	:	2029.4
		Does the component have AI to send data generated?	:	No
		Expiration date of Warranty	:	10-02-26
		Duration of Warranty	:	1 year
		Supplier Name	:	GO 3D
		Lead Time (range)	:	1 week
		Add any extra Identification Parameters (if required)	:	Only useful for 1.75 mm filament dia
Characteristics	Classification of component	Type of Operation		3D printing
		Any Sub Operation		NA
Schedule	Working Schedule for component	Working schedule		24/7
		Maintainance schedule		4 months
Relationship	Static Relationship for component and other manufacturing elements	PLA filament is passing through the nozzle from extruder		
		NA		
		NA		
Description	Additional information and explanation about the static information of component	Cold replacable not like other (hot replaceble)		

Figure 53: Static details of Go3D Artish 700 Nozzle filled by Design Engineer

From figures 29 to 33, the information of the Go3D Artish 3D printer nozzle was recorded, trying to include as much corresponding information as possible. This information is a basic understanding of the component structure and functionality. If the performance properties of this component differ between companies, this recorded information will enable future research designed for particular industrial environments, allowing customized solutions to be formulated on the basis of outcomes. The respective data was entered into the respective sheets systematically, with provisions made for entering more information as necessary.

Component	Extruder	3D Printer		
Static Information for the component				
Attribute	**Description**	**Examples**		
Identification	Information to identify component	Model No	:	E3D
		Part No	:	Revo Hemera XS
		Serial number	:	NA
		Printing Temperature Max	:	300
		filament Diameter	:	1.75mm
		Dimensions	:	85.5 x 28.9 x 65.5 mm
		weight	:	256.25gms
		speed		7000rpm
		voltage		12V/24V
		step angle		1.8
		Material	:	Aluminium, Nylon cover, Stainless steel gear, acetal idler
		Price	:	10696.74
		Does the component have AI to send data generated?	:	NA
		Expiration date of Warranty	:	10-02-26
		Duration of Warranty	:	1 year
		Supplier Name	:	GO 3D
		Lead Time (range)	:	1 week
		Add any extra Identification Parameters (if required)	:	Do not remove the grease from the drive gears
Characteristics	Classification of component	Type of Operation		3D Printing
		Any Sub Operation		Extrusion
Schedule	Working Schedule for component	Working schedule		24*7
		Maintainance schedule		after one year
Relationship	Static Relationship for component and other manufacturing elements	Extruder is lying above the nozzle allowing PLA to pass through		
		NA		

Figure 54: Static details of the Extruder in Go3D Artish 700

Component	Belt	3D Printer		
Static Information for the component				
Attribute	**Description**	**Examples**		
Identification	Information to identify component	Model No	:	GT 2 Timing Belt
		Part No	:	NA
		Serial number	:	NA
		Dimensions (Design)	:	pitch 2 mm
		Material	:	Rubber + Fibre
		Weight	:	15gms
		Price	:	99
		Does the component have AI to send data generated?	:	No
		Expiration date of Warranty	:	NA
		Duration of Warranty	:	NA
		Supplier Name	:	Robocraze
		Lead Time (range)	:	3-7 days
		Add any extra Identification Parameters (if required)	:	Look out for belt elongation after 1 year
Characteristics	Classification of component	Type of Operation		
		Any Sub Operation		
Schedule	Working Schedule for component	Working schedule		24/7
		Maintainance schedule		Manually tightening can be done
Relationship	Static Relationship for component and other manufacturing elements	Two belts holds two gears on both sides of x,y axes		
		NA		
		NA		
Description	Additional information and explanation about the static information of component	check the belt after 1 year or any disruption in product quality		

Figure 55: Static details of the Timing Belt in Go3D Artish 700

Component	Slider	3D Printer		
Static Information for the component				
Attribute	**Description**	**Examples**		
Identification	Information to identify component	Model No	:	Iwin
		Part No	:	NA
		Serial number	:	NA
		Dimensions (Design)	:	NA
		Material	:	Cast Iron
		Price	:	NA
		Does the component have AI to send data generated?	:	NO
		Expiration date of Warranty	:	NA
		Duration of Warranty	:	NA
		Supplier Name	:	NA
		Lead Time (range)	:	NA
		Add any extra Identification Parameters (if required)	:	Print quality check - skewness
Characteristics	Classification of component	Type of Operation		3D Printing
		Any Sub Operation		
Schedule	Working Schedule for component	Working schedule		24/7
		Maintainance schedule		every 3 to 4 months
Relationship	Static Relationship for component and other manufacturing elements	The slider is the part on which the axes are slid with the help of a belt driven motor		
		NA		
		NA		
Description	Additional information and explanation about the static information of component	There are balls on both sides of each slider and they can wear too. Can be based on product quality		

Figure 56: Static details of the slider in Go3D Artish 700

Process	Type of Operation	3D printing		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Information to identify Process	Process Identifier		3D Printing
Characteristics	Classification of component	Production		Yes
		Maintenance		NO
		Quality Test		NO
		Inventory		NO
		Milling		NO
		Drilling		NO
		Additive		Yes
Schedule	Working Schedule for Process	Periodic		Continuous
		duration	24	hours
		Runs	NA	Nos
		Pause time	NA	Sec
		Frequency	24/7	days
		Speed	60	mm/sec
			NA	mm/sec
			NA	mm/sec
		Travel	NA	mm
Relationship	Static Relationship for process and other manufacturing elements	NA		
Description	Additional information and explanation about the static information of process	NA		

Environment	During the Process	3D printing		
Static Information				
Attribute	**Description**	**Examples**		
Identification	Person who is operating the environment	Person 1		
Characteristics	Classification of Environment	Temperature	25-27	degrees
		Humidity	NA	# units
		Illuminance	NA	# units
Schedule	Working Schedule for environment	Periodic		# One time
		duration	24*7	hours
		Pause time	0	sec
		Frequency	0	days
Dynamic Information				
Attribute	**Description**	**Examples**		
Location	Location information (geographical / relative location)	3D Printer is in ICU setup room		
Submit	YES			

Figure 57: Details of the Process and Environment in Go3D Artish 700

Data Collection Sub Entity			
Type	Web Scraping		
Link	C:\Users\gtman\OneDrive - IIT Indore\Digital Twin\Web Scraping Code\scrapTest.py		
		Submit	YES

Figure 58: Data collection sheet for Go3D Artish 700

The data collected for the Go3D Artish 700 was through the web scraping technique. And the storage of the data was mentioned in the above link column to retrieve the data whenever used by the Python script for developing the digital twin.

Presentation				
Items to be Displayed	Line Graph	Position	x axis	time
Items to be Displayed	Line Graph	Position	y axis	time
Items to be Displayed	Line Graph	Position	z axis	time
Items to be Displayed	Line Graph	temperature	time	degrees
Items to be Displayed	Line Graph	temperature	position	degrees
Items to be Displayed	Line Graph	feed rate	extruder movement	time
Items to be Displayed	Separate Line	Time	Total Time Usage of machine	hours
Items to be Displayed	Separate line	Action	Alert	Message
Items to be Displayed	Separate line	Realtime	Timestamp	date and time
Items to be Displayed	Status of DT	Learning	Yes	No
Items to be Displayed	Status of DT	Learning count		Nos
			Submit	YES

Figure 59: Details required for Go3D Artish 700 dashboard

These are the details filled by the product manager to display specific details for the specific user roles. But for testing purposes, the details that were taken into consideration were utilization, maintenance, and production. These were selected among all the other parameters because they are important factors that affect the physical components of the printer.

Reporting	
From	Production Line
To	Admin
	Technical Supervisor
	Production Manager
Submit	YES

Figure 60: Details of the user roles to be created to display specific information of Go3D Artish 700

Referring to the above figure, the selected roles were admin, product manager, and Technical Supervisor. These were selected because in any industry, these roles were common and standard.

Plug & Play Support FE	
Connection	YES
Communication Protocol	TCP/IP
Server address	192.168.31.28
Submit	YES

Figure 61: Details of communication between the Go3D Artish 700 and the user system (PC)

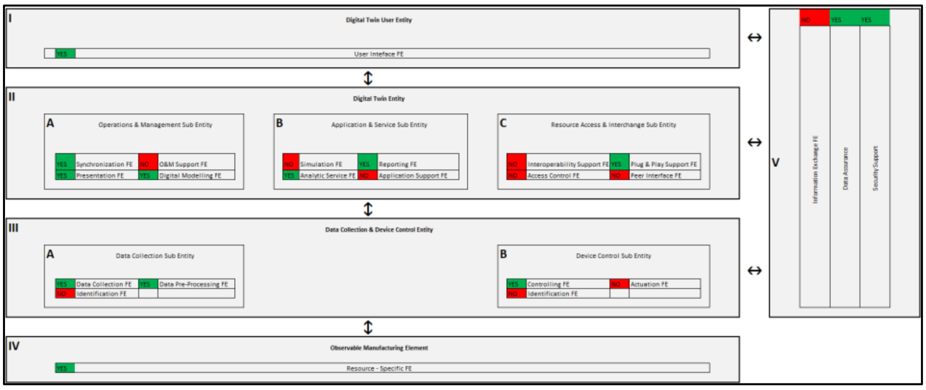


Figure 62: Overview of Go3D Artish 700 DT Setup Tool

Overview of the Digital Twin Setup Tool after filling in the details by the respective domain experts looks like the above figure. The red color box indicates that the details were not filled in by the respective domain expert. The green color indicates that the information is captured and ready to use to develop the digital twin.

5.3 Digital Twin Dashboard for Go 3D Artish 700 3D Printer

This section introduces an all-encompassing digital twin interface created for the Go 3D Artish 700 Printer. The dashboard is constructed to monitor utilization, maintenance, and production parameters in a time-segmented manner—Past, Present, and Future, enabling a full-cycle overview of the machine's behavior.

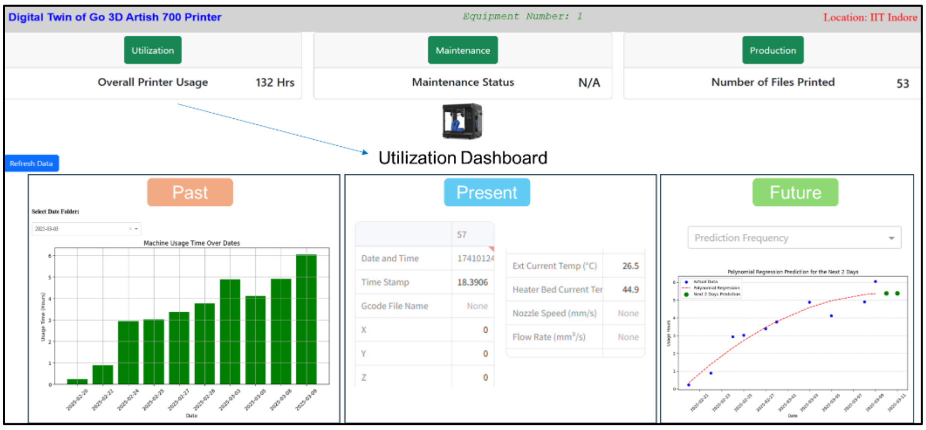


Figure 63: Go3D Artish 700 Digital Twin dashboard displaying the utilization for the Technical Supervisor role

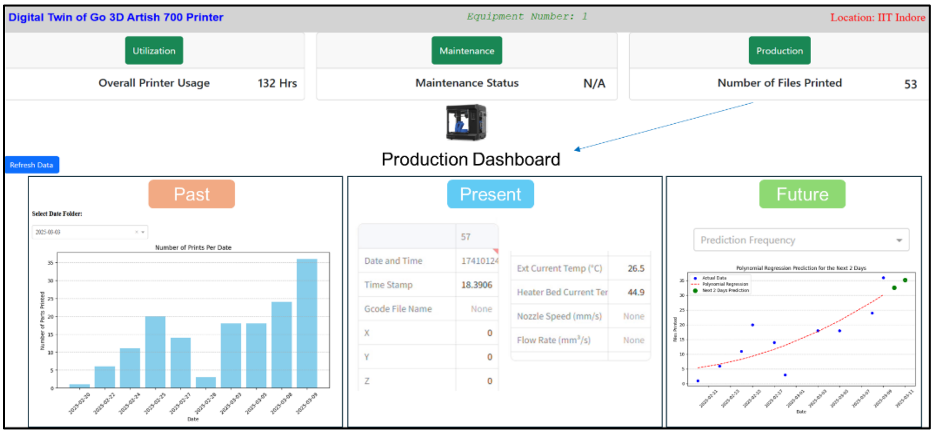


Figure 64: Go3D Artish 700 Digital Twin dashboard displaying the production for the Technical Supervisor role

Figures 59 and 60 depict the user interface of the digital twin dashboard, focusing on Utilization and Production views, respectively.

Figure 59 shows the Utilization Dashboard, which is further divided into three sections. They are Past Panel (Left), which shows the machine usage time across different dates in a bar chart, supports historical data selection through a calendar dropdown, and facilitates identification of usage trends, operational peaks, and downtimes. Present Panel (Middle), which demonstrates real-time values of timestamp, G-code file name, Nozzle X, Y, Z coordinates, the extruder temperature, and the heated bed temperature. Allows the user to carry out real-time diagnostics and ensure proper functioning during prints. Future Panel (Right), which applies Polynomial Regression for predicting machine usage frequency, enables planning and scheduling of upcoming printing jobs and maintenance activities, and this dashboard provides data-driven insight into the machine's past usage and short-term usage forecasts.

Figure 60 shows the Production Dashboard, with analogous layout rationale as the Utilization Dashboard but oriented to print file statistics. Past Panel (Left), which shows a bar graph of print jobs run per day, analysis of workload trends, project pace, and productivity is enabled. Present Panel (Middle), which has real-time information on the current print job, including print file name, current timestamp, positional coordinates, nozzle and bed temperatures, feed rates (when appropriate), and critical for live production monitoring and parameter compliance assurance. Future Panel (Right), which predicts the volume of files to print based on past trends, aids in predictive workload balancing and planning for resources in future prints. All this makes up the Production Dashboard, a tool critical for monitoring and optimizing 3D printing output.

Though not comprehensively visualized in the snapshots, the Maintenance module finds a central position in both dashboards. It acts as a connector between the Production and Utilization perspectives, offering hardware condition alerts, notifications for extruder or bed anomalies, history of maintenance cycles completed. The integration supports ensuring that usage and production statistics complement machine health so as to allow predictive maintenance strategies.

Go 3D Artish 700 Printer Digital Twin is an end-to-end tool for connecting the physical and digital worlds of 3D printing. By using easy-to-use dashboards divided into utilization and manufacturing facets, users are equipped with visibility, traceability, and predictability. The three-tiered Past–Present–Future model provides great machine management, allowing wiser decisions and fewer manual interventions.

Differences were observed while using the DT setup tool for both case studies are shown in the table below.

Table 5: Differences observed while using DT Setup Tool for Go 3D Artish 700 Printer & Ball Screw

Attributes	**Go 3D Artish 700**	**Ball Screw**
Decision making	Utilization monitoring, Production monitoring	Utilization monitoring, Backlash monitoring, Remaining useful life (RUL)
Data	Position of Nozzle (x, y, &z), Temperature, flow rate, etc.	Vibration (x, y, &z directions)
Data collection method	Multiple Experts' input needs to be taken into consideration for creating the DT Setup Tool	Multiple Experts' input needs to be taken into consideration for creating the DT Setup Tool
Frequency	Manager - Per day/week, DAQ Engineer - Continuous, Maintenance - every 3 to 4 months, Design Eng - after 1 life cycle	DAQ Engineer - 3hrs for every 3 days, Maintenance - 6 months, Sampling Rate – 1617 Hz

Data type	Integers, String, Float, Date Time	Date Time, Float, Integers
Maintenance time	Once in 3 to 4 months (for specific Parts – Lead Screw & Slider Greasing, Nozzle Cleaning)	Once in 6 months

Chapter 6 - Conclusion & Future Scope

6.1 Conclusion

The use of the ISO 23247 standard to develop Digital Twins proved to be highly effective because of its customizable structure of use, user-focused design, and standardized vocabulary that immensely facilitated multidisciplinary teams in communicating effectively. The standard ensured that Digital Twins were systematically and structurally developed for different stakeholders with distinct technical inclinations.

A scalable, modular, and highly reliable Digital Twin Setup Tool tailored to the ISO 23247 framework was created. The tool is highly integrable with various industrial settings. It provided unbroken data acquisition, model creation, and real-time monitoring with a foundation for the effective application of digital twins.

The tool was validated and tested using two industry case studies:

- Go3D Artish 700
- Ball Screw Assembly

In both instances, the solution was able to ingest all the data streams required to construct dynamic and reliable Digital Twins. Additionally, role-specific visualizations were created and deployed, providing tailored dashboards customized for different users, including:

- Product Manager
- Technical Supervisor

These dashboards were able to provide real-time visibility into machine health, operating performance, and predictive maintenance notifications. Its modularity made it simple to understand and navigate, regardless of what technical expertise.

Overall, the Digital Twin architecture proposed here reflects a real leap in digital manufacturing technology. Not only is it internationally standard compatible, but it also has cross-functional usability, scalability, and preparedness to further integrate and be utilized in Industry 4.0.

6.2 Future Work

The present work lays the groundwork for a modular and scalable Digital Twin (DT) Setup Tool based on the ISO 23247 standard. While the tool had been demonstrated useful in actual case studies, there is ample scope for improvement and enlargement in order to take full benefit of the resources of digital twins in smart manufacturing systems.

The following research directions in future are suggested:

1. Standardized Multi-disciplinary Data Sharing Mechanism

   According to ISO 23247, an even more structured data sharing framework between multidisciplinary teams—industrial, software, electrical, and mechanical engineers—will be established. This will improve integration, traceability, and cooperation, particularly in large industrial installations where interoperability is the biggest issue.

2. Autonomous Feedback and Closed-Loop Control Systems

   Future releases of the DT Setup Tool will have real-time, closed-loop control capability. This addition will enable independent process compensation based on real-time feedback from the digital twin, which will result in adaptive manufacturing and intelligent decision-making without human intervention.

3. Scalability through Multi-device and Cross-platform Compatibility

   To accommodate a wide range of machines and industrial uses, the tool will be optimized to support cross-platform use. This will require limited setup procedures for configuration, facilitating easy deployment across various devices and systems in heterogeneous environments.

4. Cloud-Native Architecture for Remote Monitoring

   Upgrading the current digital twin infrastructure to cloud-native is on priority. The transition will facilitate real-time remote monitoring, scalable deployment, continuous integration/updates, and collaborative analytics—thus increasing operational responsiveness and transparency.

5. Enhanced Role-based Visualization and Custom Dashboards

   Future development will focus on extending the visualization ability to other stakeholders such as maintenance engineers, plant supervisors, and data analysts. These role-based dashboards will contain personalized alerts, KPIs, and insights based on user responsibility and need.

6. Digital Twin Template Marketplace or Library

   To promote reusability and reduce time to develop, a digital twin template library for common industrial components (e.g., motors, actuators, 3D printers, and conveyors) will be created. The library will be modular so that plug-and-play configurations are supported and thus accelerate deployment in new applications.

7. Integration for Sustainability and Energy Analytics

   Future enhancements will also encompass modules that track and report energy consumption, emissions, and environmental impacts. These modules will drive organizational sustainability efforts and compliance with global energy standards.

The creation and implementation of a modular, ISO 23247-compatible Digital Twin Setup Tool is a milestone in the utilization of smart manufacturing. The study demonstrates the effectiveness of the tool through two industrial case studies that differ from each other—Go3D Artish 700 and the Ball Screw Assembly—and thereby establishes the scalability, flexibility, and practical relevance of standardized digital twin architectures. The system not only supported real-time monitoring and predictive maintenance but also user-specific visualizations that helped stakeholders make better decisions, such as product managers and technical supervisors.

The ISO 23247 implementation offered a systematic, interoperable, and multidisciplinary-focused architecture that highly improved team collaboration and deployment productivity. Further, the future directions outlined—diverse from individual control systems and cloud-native infrastructure to sustainability analytics and a reusable digital twin template marketplace—are a good starting point for the next phase of this effort.

In conclusion, this digital twin approach is not just a theoretical model but a real, adjustable, and expandable solution for Industry 4.0 facilities. It introduces a new benchmark for integrating physical assets with digital smarts, automating operational excellence, inter-disciplinary collaboration, and sustainable long-term growth

Chapter 7 - References

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