Standardized implementation of digital twins in manufacturing

MS (Research) Thesis

By

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DEPARTMENT OF MECHANICAL ENGINEERING

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **STANDARDIZED IMPLEMENTATION OF DIGITAL TWINS IN MANUFACTURING** in thefulfillment of the requirements for the award of the degree of **MASTER OF SCIENCE (RESEARCH)** and submitted in the **DEPARTMENT OF MECHANICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from August 2021 to June 2023 under the supervision of Prof. Bhupesh Kumar Lad, Professor, Indian Institute of Technology Indore and Prof. Makarand S. Kulkarni, Professor, Indian Institute of Technology Bombay

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.

28/06/2024

Signature of Student with date

Vedant Rade

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

28/06/2024

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28/6/24

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Makarand S. Kulkarni

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DEDICATION

I dedicate this thesis

To

My beloved Family

My friends

and

My guide

Abstract

Industries are observing massive transformation due to the advent of the fourth industrial revolution which is all about empowering traditional production systems with capabilities like machine intelligence and autonomous decision-making to facilitate collaborative production between machines and humans. Hence, researchers, scientists, and many industrial organizations are working on numerous technologies to transform existing production systems. Digital twin (DT) is one of such key technologies that facilitates this collaboration and thus helps in realizing a network of more efficient, reliable, and optimized production systems. A DT is a fit-for-purpose digital representation of a physical object or process, along with the means to permit the physical instance and the digital instance at a suitable rate of synchronization [1]. Despite the great potential of DT technology, there are significant challenges associated with its implementation. One major challenge is the lack of standardization in DT development. Because DTs can be used to simulate a wide variety of physical systems, there is no one-size-fits-all approach to creating them. This lack of standardization can make it difficult for companies to develop and share DTs, which can slow down the adoption of the technology. Moreover, the literature related to this technology primarily focuses on the proof of concepts and potential areas of application. Implementing a digital twin involves understanding of multiple disciplinary technologies while managing a variety of industrial assets. Numerous interactions with a variety of industries have also shown that the current state of DT development in industries is mostly focused on 3D visualisation and basic analytics. Predictive analytics, agent-based modelling, simulation, and the optimisation of industrial assets, among other topics, have been the subject of separate studies. However, these topics are not typically developed considering a DT architecture.As a result, not many industrial cases and/or laboratory scale demonstrations are available in literature focusing on standardized implementation of DT for various applications.

The requirement for a standardised DT creation process that concentrates on DT architecture is the answer to overcome these difficulties experienced during DT deployment. Standardization of the DT creation process is essential for the effective implementation of DT technology in manufacturing systems by streamlining the development, reducing expenses, and eventually increasing

accessibility to small and medium-sized enterprises. Furthermore, it can facilitate collaboration and sharing of DT models across disparate manufacturing systems. The thesis proposes a standardized DT creation process in the manufacturing domain that aligns with the ISO23247 framework, which guarantees that the DTs created conform to specific standards, thus allowing their seamless integration with manufacturing-related applications, such as MES and ERP. The thesis also explores two use cases where this process has been implemented in the creation of DTs. The first case study presents a DT for collaborative production, which involves the implementation of DTs in a lab environment using industry-grade hardware. The second case study presents a DT for quality control in the torquing process of joints in an automotive industry in India. The thesis work addresses the challenge of lack of standardization in implementing DTs in manufacturing by proposing a solution in the form of a DT creation process. Additionally, it contributes two case studies that comprehensively highlight the implementation process of DTs, enhancing the existing body of knowledge in this field.

LIST OF PUBLICATIONS

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ABBREVIATIONS

DT	Digital Twin
IoT	Internet of Things
AI	Artificial Intelligence
ML	Machine Learning
HMI	Human Machine Interface
MES	Manufacturing Execution System
ERP	Enterprise Resource Planning
ROI	Return On Investment
NC	Numerical Control
RUL	Remaining Useful Life
CPS	Cyber-Physical System
CNC	Computer Numerical Control
AMS	Autonomous Manufacturing System
PMDT	Production Manufacturing Digital Twin
CNP	Contact Network Protocol
EPHM	Equipment Prognostics and Health Management
MAS	Multi-Agent System
IDTS	Intelligent Digital Twin Shop floor
FE	Functional Entity
PLC	Programmable Logic Controllers
OPC UA	Open Platform Communication Unified Architecture
MQTT	Message Query Telemetry Transport
OME	Observable Manufacturing Element
DCDCE	Data Collection and Device Control Entity
KPI	Key Performance Indicator
AR	Augmented Reality
HTTP	Hyper Text Transfer Protocol
SQL	Structured Query Language
O&M	Operation and Management

NOMENCLATURE

C_p	Process Capability Ratio
C_{pk}	Process Capability Index
UCL	Upper Control Limits
LCL	Lower Control Limits
$\bar{R}$	Average Moving Range
σ	Standard Deviation
C_{pu}	Process Capability based on upper specification limit
C_{pl}	Process Capability based on lower specification limit
USL	Upper Specification Limit
LSL	Lower Specification Limit
$\bar{X}$	Average of a dataset

Chapter 1

Introduction

In recent years, industries across the globe have been transforming rapidly towards Industry 4.0, which is characterized by the integration of advanced technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) into their operations. The implementation of these technologies has helped industries to achieve higher levels of automation, efficiency, and productivity. One such technology that has gained significant attention in the industry 4.0 transformation is the Digital Twin (DT). DT is a virtual replica of a physical system, process, or product that simulates its behaviour and performance with appropriate rate of synchronization. DT can provide a wide range of benefits, including reducing costs, increasing efficiency, improving quality, and enabling predictive maintenance.

However, the implementation of DT has its challenges, including the lack of standardization, dealing with diverse industrial assets, working with multiple interdisciplinary technology aspects. These challenges make it difficult for enterprises to adopt DT technology which eventually hinder the utilization of DT across different manufacturing systems. By streamlining the DT creation process and enabling researchers to easily integrate a wide range of tools and technologies with DT, they will be able to increase the value that DT adds to the working environment. Laboratory scale validations and industrial case studies emphasising standardised DT implementation for real-world systems are essential in this regard.

As a part of the solution, a standardized DT creation process is proposed that enables developers to develop standard DTs in manufacturing irrespective of any specific case. The process also allows the developer to address common challenges encountered in DT creation at the right point in time. The proposed process is supported and validated by two case studies. The first case study involves the creation of DT for quality control in the torquing process in an automotive industry. This case was completed in an industrial environment in collaboration with John Deere. The second case study involves the creation of

DT for two station virtual machining setups enabling collaborative production in a lab environment using industry-grade hardware.

1.1 Digital Twin Technology

Digital twin technology is a contemporary phenomenon in the manufacturing domain that has gained substantial recognition in recent times. In simple terms, it is a virtual replica of a physical system developed through an amalgamation of data, analytics, and simulation tools. This virtual representation replicates the behaviour and performance of its corresponding physical counterpart in real-time, thus enabling manufacturers to gain valuable insights into the system's operation.In a recent literature [2], the authors have classified the digital objects in three categories as: digital model, digital shadow, digital twin. As shown in fig. 1, these digital objects vary in level of integration between physical and its digital counterpart.

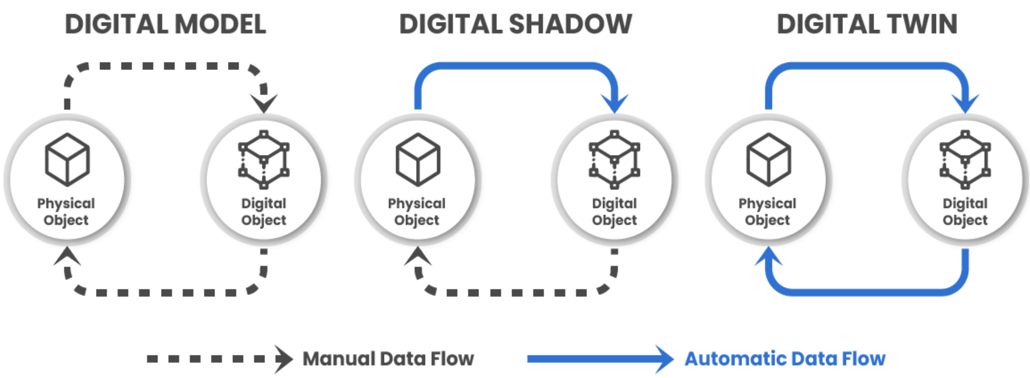


Figure 1: Classification of digital objects [3]

The working of DT involves a complex and intricate process that begins with identification of physical entity and collection of data from the entity. This data is collected using a variety of sensors and other data collection tools and includes both static and dynamic data that capture information about the performance and behaviour of the system. This data is then fed into a virtual environment where it is used to create digital entities that represent the various components of the physical system. In this virtual environment, analysis and simulations are performed on the digital twin model to predict the behaviour and performance of the physical system. This helps manufacturers to identify potential problems and make adjustments to optimize the system's performance. Additionally, the virtual environment also hosts a human-machine interface

(HMI) that displays the results of data analysis and simulations. These results can also be conveyed to other manufacturing applications, such as an MES or ERP system, which enables the system to communicate with other parts of the manufacturing process. This allows for real-time monitoring and control of the system and provides valuable insights into its operation. Finally, the results displayed on the HMI can be used by shop floor personnel to take action on the physical system, such as making adjustments to optimize performance or addressing potential problems. Alternatively, this decision making on the physical system can be automated, allowing the digital twin to make autonomous decisions based on the results of data analysis and simulations.

1.2 DT – Market Trends and Opportunities

The evolution of DT technology has been a gradual and ongoing process over several decades. The concept of digital twins originated in the aerospace industry in the 1960s, where they were used to simulate the behaviour of aircraft systems. As computing power increased, so too did the potential applications of DTs. In the 1990s, DTs began to be used in the automotive industry, where they were used to simulate the performance of engines and other components. With the advent of the IoT and the increasing availability of sensor data, DTs became more sophisticated and able to model entire manufacturing systems. Today, DT technology is a key component of Industry 4.0, enabling manufacturers to create virtual replicas of their physical systems and simulate different scenarios to optimize their processes. As computing power continues to increase and new technologies such as artificial intelligence and machine learning are integrated into DTs, their potential applications are only set to grow further. The global market for DTs is currently valued between 6.9 and 8.6 billion USD, but it is projected to experience remarkable growth in the coming years [4, 5]. By 2027, the market is expected to reach approximately 73.6 billion USD, and by 2030, it is anticipated to reach a staggering 137.67 billion USD [4, 5]. The manufacturing sector is predicted to be the largest market for DTs, contributing around 110 billion USD in 2030 [6]. This exponential growth is being driven by a compound annual growth rate (CAGR) that exceeds 40% [4, 5]. These statistics underscore the increasing recognition and adoption of DT technologies across industries. Organizations are realizing the significant potential and benefits offered by DTs in terms of enhancing efficiency, boosting productivity, and optimizing processes.

Digital twin technology has become increasingly important in various industries as it offers a range of benefits such as improved efficiency, reduced downtime, and cost savings. In manufacturing, digital twin technology is used to optimize production processes, enhance product quality, and reduce waste. The technology is also being used in the energy sector to optimize energy consumption and reduce carbon emissions. In healthcare, digital twin technology is used to create personalized models of patients to improve medical treatment and diagnosis. In the logistics industry, digital twin technology can be used to optimize the flow of goods and materials through supply chains, as well as to monitor and manage the performance of vehicles and other equipment. Additionally, the technology is being adopted in the aerospace and automotive industries to improve product design and testing. Overall, digital twin technology has the potential to revolutionize various industries and transform the way we design, operate, and optimize complex systems.

1.3 Challenges to DT Technology

Implementing DTs presents a set of challenges that organizations need to overcome to fully harness the potential of this technology. These challenges can impact the successful adoption and effective utilization of DTs.

One of the key challenges is data integration. DTs rely on gathering and harmonizing vast amounts of data from various sources, including sensors, machines, and legacy systems. Integrating disparate data sets and ensuring their quality, consistency, and compatibility can be complex and time-consuming. Scalability is another significant challenge. DTs are often deployed in large-scale environments such as smart cities or complex industrial systems. Handling massive volumes of real-time data, managing computational resources, and ensuring the responsiveness and scalability of DT platforms pose technical and operational challenges. Security and privacy concerns are critical considerations when implementing DTs. Protecting sensitive data collected by DTs from unauthorized access, ensuring data privacy compliance, and addressing potential cybersecurity risks are essential for maintaining the trust and mitigating potential vulnerabilities. Interoperability is another challenge as DTs often need to interface and communicate with various systems, platforms, and protocols. Ensuring seamless integration and interoperability across different technologies, standards, and data formats requires careful planning and coordination.

Apart from these technical difficulties, there are other sets of challenges that hinder the implementation of DTs. Organizational culture and change management represent significant challenges. Adopting DTs requires organizational readiness and a shift in mindset, culture, and processes. Resistance to change, lack of digital literacy, and the need for workforce upskilling can hinder successful DT implementation. Cost considerations and demonstrating return on investment (ROI) are additional challenges. DT implementation involves significant upfront and ongoing costs, including infrastructure, software, data storage, and skilled personnel. Demonstrating the tangible benefits and ROI of DT projects is crucial for securing investment and long-term sustainability.

1.4 Problem Statement

Interactions with industries helped in divide DT development into following four stages.

Stage 1: 3D visualization+ Basic analytics
Stage 2: 3D visualization+ Basic analytics +Predictive analytics
Stage 3: 3D visualization+ Basic analytics +Predictive analytics+ Learning and communication capabilities + decentralized decision making
Stage 4: DT Evolution its management over entire life cycle

As far as DT development programmes are concerned, the majority of industries are currently experimenting in stage 1. Significant literature on predictive analytics, machine learning, machine-to-machine communication, and decentralised decision making is also available in parts and pieces; however, the development has not occurred with the DT architecture in mind. Therefore, any industry's DT programme must adopt a new strategy for integrating such work with DT architecture in order to extract maximum benefits from the corresponding physical asset and make it suitable to operate in a Cyber Physical Systems environment. In addition, it is essential that the DT architecture facilitate the management of DT throughout the entire life cycle of the corporeal entity. All of these factors necessitate a standardised DT creation procedure centred on DT architecture. The problem addressed in this thesis work revolves around the lack of standardized frameworks and guidelines for DT creation and implementation.

Moreover, the scarcity of literature focusing on the real-time implementation of DTs in manufacturing hinders the ability of researchers and practitioners to gain practical insights and guidance. While there are numerous studies and research papers discussing the theoretical aspects and potential benefits of DTs, there is a limited availability of comprehensive case studies and practical examples showcasing their successful implementation in real manufacturing environments. This scarcity of literature makes it challenging for organizations to navigate the complexities of DT implementation, understand the potential risks and benefits, and make informed decisions regarding their adoption.

Addressing these challenges is crucial to promote the widespread adoption and effective implementation of DT technology in the manufacturing sector. By establishing standardized frameworks and guidelines, organizations can ensure consistency, interoperability, and compatibility among different cases of DT implementations. Additionally, increasing the availability of literature illustrating real-time DT implementations will provide valuable insights and practical guidance for organizations embarking on their DT journeys. Overall, addressing these challenges will contribute to the successful integration and utilization of DT technology in industries, enabling organizations to unlock their full potential for enhanced productivity, efficiency, and decision-making.

1.5 Thesis Organization

This chapter presents abackground of the DT technology along with an overview and direction of the work presented in this thesis. Chapter 2 presents a detailed literature survey involving a review of various articles available which examine the current state of DTs in manufacturing along with the challenges associated with their implementation. These challenges have significantly helped in defining the objectives of this work. The chapter also discusses some of the solutions presented in the literature addressing the aforementioned challenges, which eventually helps in differentiating and understanding the importance of the work presented in this thesis. Chapter 3 proposes the standardized DT creation process along with the use of some of the already available standards in the field of DTs in manufacturing. Chapter 4 presents the first case study which involves the creation of DT for quality control in the torquing process of joints. This case was completed in an industrial environment in collaboration with an automotive industry in India.Chapter 5 presents the second case study which involves the creation of DT of two station virtual machining setups enabling collaborative production in a lab environment using industry-grade hardware. Chapter 6 concludes the thesis highlighting the future work in this domain.

Chapter 2

Review of past work and problem formulation

The concept of digital twin technology has rapidly gained attention in recent years due to its potential to revolutionize various industries by enabling real-time monitoring, predictive maintenance, and optimization of systems. This section provides a comprehensive review of the literature related to DTs in manufacturing, highlighting the major contributions to the development and implementation of digital twins. On the other hand, this section highlights the research gaps observed in the literature. These research gaps support the objectives of this thesis.

2.1 Literature Review

Research has focused on the development of DT for use in a variety of manufacturing contexts such as product design, condition monitoring, diagnostics, prognostics, commissioning, and operation. A process to construct a digital twin for a sheet metal punching machine to support the virtualization and facilitate the interactive design of optimal NC machining programs is presented in [7]. Similarly, a methodology for product design based on the DT is presented in [8]. Along with this, the authors also presented a case study of bicycle design based on DT. Authors in [9] presented a methodology for the creation of DT models for calculating the RUL (Remaining Useful Life) of machinery equipment using physics-based simulation models. A DT reference model for rotary machinery fault diagnosis is presented in [10]. Authors in [11] presented an experimental demonstration to build DT models for the prediction and diagnosis of CNC milling machine tools. Authors in [12] discussed a Cyber-Physical System (CPS) architecture for CNC machine tool monitoring and teleoperation. A framework of DT-driven assembly commissioning is provided in [13]. Along with this, the authors also presented a case study to discuss the construction of assembly commissioning.

Another class of work focuses on the framework, reference model, and architecture for DT. A systematic development methodology and generic system architecture for the creation of CPMT are presented in [14]. A DT architecture for a cyber-physical production system (CPPS) to support job scheduling is presented in [14]. Authors in [16] presented a DT framework comprising five major aspects which include data, services, physical, model, and connections. They also discussed the technologies and tools to implement these aspects in a DT. Similarly, a production manufacturing DT (PMDT) framework is presented in [17] which consists of 5 models: Production definition model, geometric and shape model, manufacturing attribute model, behaviour and rule model, and data fusion model. An application framework of DT for product lifecycle management is presented in [18]. This article also describes the implementation process of fully parametric virtual modelling and the construction idea for DT. Authors in [19] presented an idea of DT-driven smart manufacturing and a reference model for constructing a DT.

DT being a prominent tool in Industry 4.0, it was essential to add a new aspect to this literature review which is the collaboration in manufacturing systems using DTs.A detailed exploratory study of various machine learning algorithms like clustering, regression and probabilistic decision making is presented in [20]. An industrial multi agent system for real-time distributed collaborative prognostics addressing the challenges faced by existing systems in adapting to the dynamic and heterogenous properties of real asset fleets is presented in [21].A framework to integrate local DTs and global DTs to deal with an automatic re-scheduling process for cyber-physical production processes is presented in [22]. This article has also introduced a framework for decentralized and integrated decision-making for re-scheduling of a cyber-physical production system (CPPS) which was validated in an Industry 4.0 pilot line of the assembly process, showcasing its proof of concept. A self-organizing manufacturing network designed to achieve effective cooperation among smart workpieces and smart resources is presented in [23]. This proposed network encompasses a job-machine optimal assignment mechanism and an adaptive optimization control mechanism to improve the system's performance under disturbances. A synthetic method for building cognitive agents as autonomous control entities in a manufacturing system, which are the means for developing an Autonomous Manufacturing System (AMS), possessing intelligence, autonomy, and communication characteristics for adapting to disturbances is presented in [24]. A reactive decentralized coordination mechanism for collaborative production planning decisions is introduced in [25]. This article also presents a case study that illustrates the development, and implementation of a smart factory prototype that encompasses the key elements of a smart factory. A self-organizing negotiation mechanism based on the contract network protocol (CNP) for guiding cooperation and competition among multiple agents, and supporting intelligent decision-making is proposed in [26]. The paper also establishes a decision-making module, called the artificial intelligence (AI) scheduler, for the equipment agent using a multi-layer perceptron, which enables the manufacturing equipment to generate an optimal production strategy based on the perceived workshop state. A DT-enhanced dynamic scheduling methodology is presented in [27]. The effectiveness of this methodology is highlighted with the help of a case study involving the making of hydraulic valves in a machining job shop. A job shop scheduling mode and its implementation on the prototype system, architecture, and working principle along with the resource parameter updating methods and dynamic interactive scheduling strategies to achieve real-time and accurate scheduling is presented in [28]. A proof-of-concept framework is presented for robust scheduling in a Flow Shop Scheduling Problem which utilizes genetic algorithms and discrete event simulation and is synchronized with a Digital Twin (DT) equipped with an Equipment Prognostics and Health Management (EPHM) module [29]. An Agent-Based Collaborative Production System based on a real-time order-driven approach is presented, which optimizes production planning and scheduling strategies in response to external disturbances [30]. The proposed system is tested through simulation prototypes and experiments, providing a promising solution for manufacturers to make quick and correct decisions in dynamic marketing environments. A novel bi-level distributed dynamic workshop scheduling architecture is proposed, which involves leveraging a workshop digital twin scheduling agent and multiple service unit digital twin scheduling agents [31].

A distributed collaborative prognostics tool utilizing multi agent systems and machine learning to provide real-time tailored prognostics and maintenance recommendations for industrial assetfleets in non-ergodic and dynamic conditions is presented in [32].The use of a Cyber-Physical System (CPS) and Digital Twin technologies for interconnecting and interoperating a physical shop floor with a cybershop floor is introduced in [33]. A Multi-Agent System (MAS) architecture for collaborative learning is presented and implemented for a prognostic problem in [34]. The proposed architecture involves collaboration among assets through the calculation of inter-asset similarity during operating conditions to identify clusters of "friends" and facilitate sharing of operational data within these clusters. An Intelligent DT shop floor (IDTS) architecture is presented in [35]. Further, the article also highlights the development of a self-organizing and self-adaptive model which showcases the construction of intelligent manufacturing systems. A novel Elman-IVIF-TOPSIS model to improve collaboration between stakeholders in a smart manufacturing environment enabling manufacturing enterprises to respond quickly to market change and reducing the loss of manufacturing resources and operating costs is presented in [36].

2.2 Research gaps

The literature on digital twin development for manufacturing systems reveals that DTs are usually tailored to specific cases, making integration with other manufacturing management systems a challenging task. Authors in [19] have identified standardization as a critical research issue in DT development and application and thus standardization of DT implementation in manufacturing systems is the only viable solution to bridge this gap. Efficient and standardized integration with internal systems, such as MES and ERP used on shop floors, is essential for achieving greater operational efficiency and visibility. In addition, DTs must be capable of communicating with peer DTs and external applications to facilitate diagnostics, prognostics, and autonomous decision-making. This requires architecture oriented standardized DT creation process.

Literature involving limited real-life implementation of DTs adds to this problem of standardization. Although various frameworks and architectures for DTs have been proposed in the literature, they primarily emphasize models for DTs, without adequately addressing issues related to DT integration with other systems and applications in manufacturing. It is observed researchers and industry practitioners are significantly focusing not only on developing specific intelligent functions but also on integrating them into CPS [14]. However, these DT development process facilitating integration of such approaches with DT architecture is limited in literature.

These challenges limit the scalability and efficiency of DTs and hinder their ability to enhance operations in manufacturing systems. Therefore, there is a need for more standardization in the creation of DTs and an architecture oriented process. By addressing these challenges, this research aims to enhance the implementation of DTs in manufacturing systems and enable their widespread adoption.

2.3 Research objectives

1. Develop a standardized process for the creation of DTs in manufacturing systems that aligns with the ISO23247 architectural framework, thereby addressing the current lack of standardization in the field which will enable more efficient integration with existing manufacturing management systems.
2. Demonstrating the implementation of proposed process for an industrial case to showcase and validate the effectiveness of the proposed process in an industrial environment.
3. Demonstrating the implementation of proposed process to showcase collaborative production using DTs in laboratory environment.

Chapter 3

DT creation process

In the realm of digital twin implementation, various functionalities such as predictive analytics, machine-to-machine communication, AI/ML, and decentralized decision-making have been explored independently, lacking a centralized focus on the DT creation process and architecture. This fragmented approach has resulted in a lack of standardization, integration, and effective implementation of digital twins in the industry. Existing works are often disjointed and fail to support a cohesive DT implementation. To address this challenge, this chapter presents a standardized DT creation process that streamlines the development of digital twins by providing a structured framework. This proposed process aims to overcome the limitations of existing approaches and facilitate the wider adoption and successful implementation of digital twins in real-world manufacturing scenarios.The process is divided into three broad stages: scope identification, system analysis, and DT development. The subsequent sections will provide detailed insights into each stage, exploring the specific activities and considerations involved.

3.1 Scope Identification

Digital twins possess remarkable versatility and efficacy in addressing challenges across various production systems. However, to ensure their effectiveness, it is crucial to define the scope of the digital twin accurately. As previously defined, a digital twin serves as a purpose-built digital representation of a physical object or process. Consequently, the scope of the digital twin relies on its intended purpose, dictating the specific considerations that need to be addressed.

The scope identification process encompasses determining the physical object for which the digital twin will be developed, specifying the functionalities that the digital twin will encompass, identifying the necessary data collection requirements, and determining the end users of the digital twin. The physical objects could vary from individual equipment, such as the gearbox described in [9], to complex processes like the micro injection moulding process highlighted in [37]. Functionality aspects of the digital twin may involve prognosis capabilities, such as vessel-specific fatigue damage monitoring and prognosis described in [38], visualization capabilities as demonstrated in [7], or even product design functionalities exemplified in [8].

To adequately represent the physical objects, the digital twin necessitates collecting both static and dynamic information attributes. The ISO 23247 standard provides a comprehensive information model for these attributes. Static information attributes encompass essential details such as identification, characteristics, schedule, relationships with other manufacturing elements, and descriptions. On the other hand, dynamic information attributes encompass real-time status, location, reporting, relationships with other manufacturing elements, and descriptions.

Additionally, defining the scope of the digital twin entails identifying the end users who will benefit from its functionalities. These users may include peer digital twins, as suggested in [39], manufacturing management systems such as MES and ERP, as emphasized in [40], or other customized applications designed to leverage the capabilities of the digital twin.

In conclusion, the scope identification stage plays a pivotal role in the development of a digital twin. By carefully determining the purpose, physical object, functionality, data requirements, and end users, organizations can ensure the digital twin's relevance, effectiveness, and successful integration within the manufacturing ecosystem. The subsequent stages of the digital twin creation process are built upon this scope, shaping the system analysis and development methodologies to create a robust and fit-for-purpose digital twin solution.

3.2 System Analysis

The system analysis stage is a crucial step in the DT creation process as it allows for a comprehensive understanding of the operations of the physical system and the communication network. By analysing these aspects, data sources and extraction methods can be determined to facilitate the development of the DT. This section will discuss the analysis of system operations and the analysis for the communication.

3.2.1 Analysis of the Operations

The analysis of system operations involves gaining a thorough comprehension of the activities and processes occurring within the physical object. It is essential to understand how the physical object interacts with auxiliary manufacturing management systems, such as Manufacturing Execution Systems (MES) or Enterprise Resource Planning (ERP) systems. This understanding provides insights into the interactions and dependencies between the physical object and the systems that manage its operation. By examining the workflows, processes, and functionalities involved, organizations can capture the essential aspects that need to be represented in the DT.

During the analysis of system operations, it is important to consider the data generated during the system's operations as input for the DT's functionality. This data serves as a valuable source of information for capturing the behaviour and performance of the physical object. By identifying the relevant data points and differentiating them from irrelevant ones based on the predefined scope of the DT, organizations can ensure that the DT accurately represents the desired aspects of the physical system. This analysis helps in determining the specific data attributes and parameters that need to be collected and monitored to ensure an accurate representation of the physical object within the DT.

3.2.2 Analysis for Communication

System analysis for communication focuses on establishing efficient communication channels between the DT application, the physical object, users, and other auxiliary applications like database applications. Communication is a critical aspect of the DT, as it enables real-time data exchange, synchronization, and interaction between the various components involved. To achieve effective communication, it is necessary to explore the most suitable and efficient means of communication based on the available network of hardware and software.

Understanding the network infrastructure is crucial for designing and implementing a robust communication network. This includes examining the existing hardware components, such as Programmable Logic Controllers (PLCs), controllers, sensors, and smart actuators, and their capabilities for data acquisition, control, and transmission. Additionally, the software applications used in the manufacturing environment, such as MES, ERP, and database applications, need to be considered when establishing the communication network.

The selection of appropriate communication protocols is vital for ensuring seamless and secure data exchange. Protocols like OPC UA (Unified Architecture) and MQTT (Message Queuing Telemetry Transport) are commonly used in industrial settings for efficient and reliable communication. These protocols provide standardized methods for data exchange, ensuring compatibility and interoperability between different systems and applications.

Once the relevant tools and technologies for communication have been identified, the next step is to establish the communication network. This involves configuring the communication protocols, setting up hardware devices, and implementing the necessary software interfaces. It is essential to ensure that the communication network is reliable, scalable, and capable of handling the required data volume and frequency. Organizations need to consider factors such as data transmission speed, latency, security, and data integrity when designing and implementing the communication network.

By carefully analysing the communication requirements and leveraging suitable tools and technologies, organizations can create a well-integrated and efficient communication network for their DT implementation. This network enables seamless data exchange, real-time monitoring, and collaboration between the DT, the physical object, and other applications. It forms the foundation for the successful implementation and operation of the DT, facilitating accurate representation and synchronization between the physical system and its digital twin.

In conclusion, the system analysis stage is a critical part of the DT creation process. By analysing system operations and communication requirements, this stage finally addresses two major questions in DT development viz., where the data will come from and how the data will come from.

3.3 DT Development

After finalizing the scope of the digital twin (DT) and conducting a comprehensive system analysis, the next crucial step in the DT creation process is the development phase. This section focuses on two main aspects: DT architecture and DT modelling. These steps are essential in ensuring a standardized and effective implementation of digital twin technology in the manufacturing domain.

3.3.1 DT Architecture

The selection of an appropriate DT architecture is paramount in achieving a consistent and coherent representation of the digital twin. Standardization plays a pivotal role in this context, emphasizing the need for a framework that can seamlessly integrate the various components of the DT and facilitate interoperability with other manufacturing-related applications.

In light of this, the ISO 23247 architecture stands out as a robust reference model specifically designed for DT development in manufacturing systems. It offers a comprehensive framework that encompasses different domain-based entities, including Observable Manufacturing Elements (OME), Data Collection and Device Control Entity (DCDCE), DT System Entity, and DT User Entity. The architecture provides a structured approach to map the functionalities and data points identified during the earlier stages of the DT creation process.

By adopting the ISO 23247 architecture, organizations can ensure compatibility, consistency, and adherence to industry standards in their DT implementations.

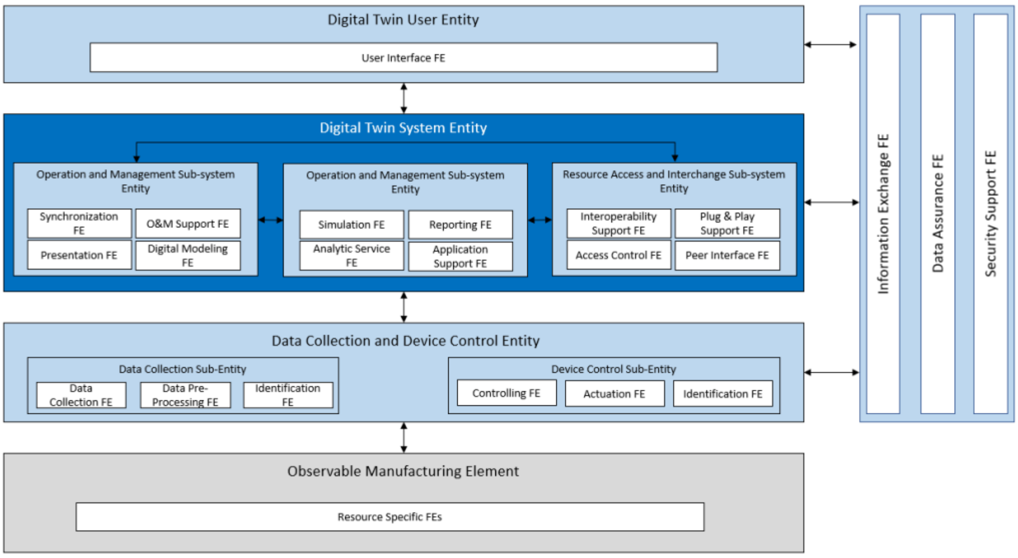


Figure 2: Functional reference architecture for the creation of DTs in manufacturing [39]

Fig.2 illustrates a visual representation of the ISO 23247 architecture, depicting the interrelationships between the different entities and their corresponding functional entities (FEs). The FEs, which are specific to each domain, play a vital role in capturing the essential characteristics and functionalities of the physical system within the digital twin environment.

3.3.2 DT modelling

Once the DT architecture is selected, the focus shifts to DT modelling. This stage involves creating the necessary sub-entities and FEs within the architecture to fulfil the intended purpose of the DT.

The DT modelling process encompasses designing and configuring the relevant sub-entities, such as the Operation and Management Sub-system entity, Application, and Service Sub-system entity, and Resource Access and Interchange Sub-system entity. These sub-entities facilitate the overall operation, management, and accessibility of the digital twin. The key aspect of DT modelling lies in the creation of FEs that accurately represent the behaviour and functionalities of the physical system. The ISO 23247 architecture guides developing specific FEs for each domain. These FEs are responsible for executing various tasks, such as data collection, data analysis, process visualization, and communication with other manufacturing management systems.

The modelling process requires a deep understanding of the physical system and its associated functionalities. It involves configuring the FEs according to the requirements identified during the earlier stages of the DT creation process. Special attention should be given to ensuring the accuracy, compatibility, and integrity of the modelled entities, as they serve as the digital counterpart of the physical system.

By effectively implementing the suggested FEs within the DT architecture, organizations can capture and represent the essential aspects of the physical system in the digital twin environment. The FEs enable the digital twin to perform operations, manage resources, provide services, and facilitate data access and interchange. This comprehensive modelling approach ensures that the digital twin closely reflects the behaviour, functionality, and interactions of its corresponding physical system.

In conclusion, the DT development phase involves selecting a suitable architecture, such as the ISO 23247 framework, and meticulously modelling the necessary sub-entities and FEs within the architecture. This standardized approach ensures compatibility, consistency, and adherence to industry standards in digital twin implementations.

Fig. 3 presents the proposed DT creation in the form a flow diagram for better understanding.

Scope Identification	Details
Understanding the problem statement	--
Identifying the physical object	The physical can be any kind of manufacturing element including equipment, process, personnel, product, environment, facility, etc. [41]
Identifying the Functionalities required	Functionalities in a DT can be monitoring, prognostics [38], visualization [7], product design [8].
Identifying the data required	Two category of data required: Static Information, Dynamic information [41]

System Analysis	Details
Analysis of the operations	Identifying and categorizing the data sources in static and dynamic information
Analysis for the communication	Identifying the information exchange methods around the DT application [42]

Digital Development	Details
Selecting the DT architecture	ISO 23247 functional reference architecture [39]
DT modelling	Developing the functional entities required to achieve pre defined functionalities present in the architecture

Figure 3: Flow diagram illustrating the entire DT creation process

Chapter 4

Case Study 1: DT for quality control in the torquing process of joints

This chapter presents a case study that exemplifies the practical implementation of the proposed DT creation process in an industrial context. This case study focuses on developing a DT for quality control in the torquing process of joints in an automotive industry in India. The importance of this case study lies not only in validating the proposed process but also to demonstrate the effectiveness of the standardized DT creation process proposed earlier in the thesis. By showcasing a real-life implementation, this case study serves as a valuable reference for developers seeking to utilize the standardized process in their own projects. Furthermore, the successful implementation of the DT in an industrial setting contributes to the existing literature by providing a tangible example of a real-life DT implementation, further enhancing the body of knowledge in this field.

The torquing process plays a critical role in assembly lines, ensuring that the specified torque is delivered at each joint to ensure the proper functionality of the vehicle. Various factors such as material, size, plating, surface polish, thread lubricants, corrosion, and wear of fasteners can influence the torque-tension relationship, leading to variations between the applied and specified torque. To address this issue in the automotive industry in India, a case study on the creation of a DT for the torquing process is presented in this section. This case study follows the DT creation process and architecture discussed in the previous chapter, providing insights into the implementation of DT technology to optimize the torquing process. By leveraging the principles of DT and its associated architecture, this case study aims to improve torque accuracy and enhance the overall efficiency and reliability of the torquing process in the automotive industry.

4.1 Scope Identification

Understanding the issue of torque variation emphasizes the importance of monitoring and controlling the torquing process. Real-time monitoring enables comprehensive data collection for visualization and analysis of process parameters. Analysing these parameters helps calculate Key Performance Indicators (KPIs) associated with the process, empowering operators to promptly identify and rectify any issues that arise.

In this specific case, we have opted for the implementation of a DT to address the aforementioned challenge. DTs offer real-time monitoring, analysis, and optimization of the operations involved in the OME. Traditional methods like manual inspection and data collection prove to be time-consuming, prone to inaccuracies, and susceptible to errors. Leveraging DT technology, which falls under the umbrella of Industry 4.0, allows for the integration of intelligence through cutting-edge technologies like Artificial Intelligence (AI) and Machine Learning (ML). This, in turn, facilitates autonomous and proactive process control.

To tackle the torquing process issue, our solution encompasses the following three key aspects:

1. Visualizing the torquing process and its KPIs, such as process capability ratio (C_p), process capability index (C_{pk}), run charts, and process histograms, through a web application and an Augmented Reality (AR) application.
2. Analysing variations between the designed torque and the applied torque in the torquing process.
3. Generating user recommendations to control the process effectively.

In adherence to the desired DT functionalities, data acquisition adheres to the format prescribed by ISO 23247 [41]. Information is classified into static and dynamic categories, as illustrated in Tables I, II, and III.

Table 1: Static information related to the torquing process

Attributes	Description	Sample Data
Identification	Information to identify the process	Process I1001: In the current case it was identified based on the product ID and joint ID
Characteristics	Classification of the process	Torquing process

Relationship	Static relationship for the process and other elements	Process “I1001” is managed by operator A with the torquing tool “Y”

Table 2: Static information related to the operator

Attributes	Description	Sample Data
Identification	Information to identify the operator	Operators are identified based on their Employee ID
Characteristics	Classification of the operator	Skill and certification of the operator
Schedule	Working schedule of the operator	The working hours can be divided into two or more shifts. The timing of a particular shift is the working schedule for the operator
Relationship	Designation of the operator	Operator “A” is the boss of Operator “B”

Table 3:Dynamic information related to the torquing process

Attributes	Description	Sample Data
Status	Status of the process	The status of the process can be in-process, completed, or interrupted
Report	Work report related to the process	In this case, the report of the process includes the time of completion, applied torque value, KPIs related to the process, and the recommendations generated based on the analysis

Relationship	Dynamic relationship for the process and other elements	Process “I1001” is operated by Operator “A” with the torquing tool “Y”

The end-users of the DT include the Manufacturing Execution System (MES), the AR application, and the web application. The MES leverages the DT to obtain torque predictions for specific joints and real-time process status updates. Meanwhile, the web application and AR application serve as visual interfaces for process status visualization and recommendations.

4.2 System Analysis

4.2.1 Analysis of the Operations

Initially, an assembly arrives at the workstation, and the operator proceeds to utilize a motorized torquing tool to apply the specified torque to the joints, ensuring optimal tightness. The torque value, referred to as the Designed Torque, is predetermined and recommended by the MES application. This value is calculated based on meticulous design calculations, considering factors such as material, size, plating, surface polish, and other variables that influence the torque-tension relationship. It is important to note that assemblies may consist of multiple joints, each requiring either the same or a different designed torque.

The tightening sequence of the joints is pre-established and must be strictly adhered to by the operator. However, the absence of a monitoring sensor currently impedes the ability to verify whether the operator follows the prescribed sequence accurately. Consequently, deviations in the tightening sequence cannot be promptly identified or rectified.

To facilitate the development process, the data generated during this operation is categorized and organized in Table I, II, and III. This categorization enables the developer to determine the sources from which the data will be obtained. In the present case, the MES serves as a valuable data source, providing not only static data but also additional information regarding various factors that influence the torque-tension relationship. Furthermore, real-time information, such as the applied torque value, is acquired directly from the torquing tool controller.

In terms of visualization, the limited diversity of assemblies and joint types allows for the direct storage of 3D models within the digital twin. This facilitates the seamless rendering of the models, ensuring a comprehensive and immersive representation of the torquing process.

4.2.2 Analysis for Communication

In this step, we focused on identifying the necessary communication channels within the digital twin framework. Four key instances requiring communication were identified and addressed accordingly.

The first instance involves acquiring static information about the torquing process from the MES application. Upon analysing the MES application, we discovered that it supports the MQTT communication protocol. Hence, we developed an MQTT client within the digital twin application to establish communication with the MQTT broker in the MES application [43]. This allowed us to retrieve the essential static information related to the torquing process.

In the second instance, real-time information associated with the torquing process needed to be obtained from the torquing tool controller. However, our analysis revealed that neither OPC UA nor MQTT could be directly used to collect real-time data from the torquing tool controller. To overcome this limitation, we introduced an external system between the torquing tool and the digital twin application. This external system, equipped with an OPC UA server, receives information from the torquing tools via an Ethernet Network. Subsequently, we developed an OPC UA client to communicate with this server [44]. The selection of OPC UA is motivated by its superior performance in quick-response applications and its seamless integration with legacy equipment [45].

The third instance necessitated communication between the digital twin application and the users (web and AR applications) for the seamless rendering of process parameters, analysis results, and user recommendations. To achieve this, we leveraged Express JS to develop efficient servers that utilized a combination of HTTP (Hypertext Transfer Protocol) and WebSocket protocols. These servers facilitated the seamless rendering of web files on various web browsers and catered to requests received from the HTTP client present in the AR application. By employing these standardized protocols, sustained two-way communication between the server and the client was ensured.

Finally, establishing a communication channel between the digital twin application and the database was essential to store and retrieve production-related data. For this purpose, we utilized a MySQL database application. To establish communication, we developed a MySQL client within the digital twin application [46]. This client facilitated the execution of database-related queries by communicating with the server present in the database application.

The technologies and protocols utilized, as well as their interactions, are depicted in Fig. 4, illustrating the comprehensive communication network between the digital twin and other interconnected applications.

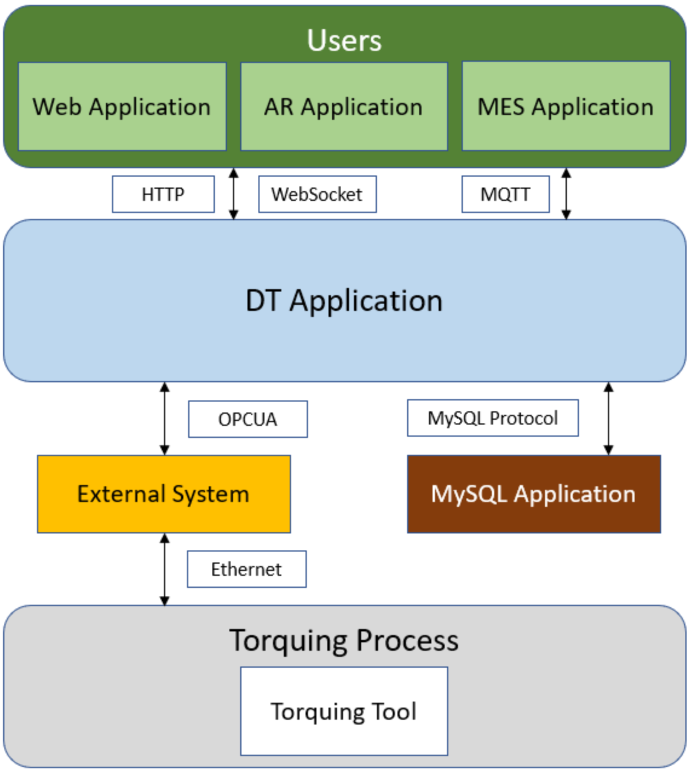


Figure 4: Communication network of DT with other applications

4.3 DT Development

4.3.1 DT Architecture

The architecture presented in Fig. 5 serves as a comprehensive mapping of the OME, users, and the various communication protocols discussed in sections 4.1 and 4.2. The architecture diagram highlights the specific sub-entities and FEs that are crucial for achieving the objectives of the digital twin application in the given context. These sub-entities and FEs play a vital role in ensuring the successful implementation and operation of the digital twin system.

In the upcoming sub-section, we delve deeper into the significance and realization of these sub-entities and FEs. By exploring their functionalities and interactions, we will gain a comprehensive understanding of how they contribute to the overall effectiveness and efficiency of the digital twin application.

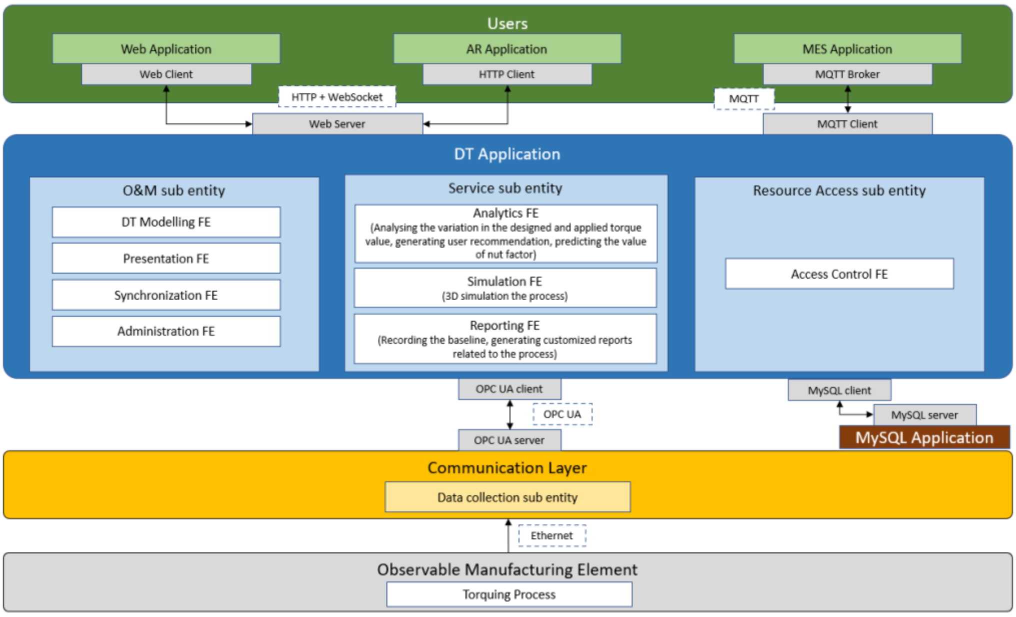


Figure 5:Customised DT architecture for quality control in the torquing process of joints

4.3.2 DT modelling

In this step, we discuss the realization of the sub-entities required for the proposed DT, based on the functional reference architecture shown in Fig.5. As depicted in the figure, the DT application consists of three sub-entities.

Operation & Management sub-entity: The Operation & Management (O&M) sub-entity in the present case encompasses several functional entities, namely digital modelling, presentation, synchronization, and administration. Let's delve into the details of each of these entities.

1. Digital modelling FE: Digital Modelling FE plays a crucial role in interpreting the data and information related to OMEs. In the present case, the digital modelling FE is responsible for analysing various parameters

such as the product ID, joint ID, applied torque on specific joints, and the overall process status (whether it is within the control limits or not). By extracting these insights, the digital modelling FE enables the creation of more precise and realistic digital representations of the torquing process. This enhances the accuracy and reliability of the digital models used for monitoring and analysis purposes.

2. Presentation FE: The Presentation FE plays a vital role in displaying the modelled digital entities in a user-friendly and interactive manner. In our case, we have employed both web and Augmented Reality (AR) applications to present the digital entities and associated data effectively. Our web application offers users a comprehensive 3D view of the torquing process, along with valuable analytics and graphical representations of process parameters and KPIs. These KPIs include metrics such as C_p and C_{pk} values, run charts, and user recommendations specific to the process. To ensure seamless hosting and access to the web application, we have utilized Express JS and HTTP protocols, guaranteeing fast and reliable data retrieval. An example page of the web application is depicted in Fig. 9, showcasing its user interface and available information. Additionally, we have developed an AR application using the Unity game engine to provide users with a convenient visualization tool. This application allows quick access to the KPIs relevant to a specific process. The AR application incorporates an HTTP client that sends requests for information and access to the functionalities of the DT. These requests are verified and processed by Express JS. By combining the capabilities of both web and AR applications, we have created an intuitive and user-friendly interface that enables easy access to critical process data and valuable insights. Overall, the Presentation FE ensures that the modelled digital entities and associated information are presented in an engaging and accessible manner, empowering users to effectively monitor and analyse the torquing process.
3. Synchronization FE: The Synchronization FE plays a crucial role in ensuring real-time synchronization between digital entities and their physical counterparts in the torquing process. Its primary function is to facilitate the seamless exchange of data and updates between the digital models and the actual torquing process. In our case, the DT application receives the applied

torque value from the torquing tool controller in real time. This data is then updated in the corresponding digital entities, ensuring that they accurately reflect the current status of the process. The Synchronization FE also serves as a channel for collecting user feedback from both the web and AR applications, allowing users to provide input and interact with the digital representations. To enable efficient synchronization and user feedback, we have leveraged the capabilities of the WebSocket communication protocol. By utilizing WebSocket in conjunction with HTTP, we ensure compatibility between the two protocols and enable bidirectional communication. This integration allows the DT application to effortlessly synchronize the status of digital entities with real-time data, ensuring that users have access to up-to-date information. With the Synchronization FE in place, the selected and applied torque values are synchronized, and run charts and other relevant data are updated in real time. This enables users to make informed decisions based on the most current data available. Additionally, the integration of WebSocket with HTTP facilitates the monitoring of user interactions on the web interface. User requests, such as initiating baseline recordings or switching tabs, are interpreted and communicated to the web servers, ensuring a seamless and interactive user experience. By incorporating the Synchronization FE and utilizing WebSocket and HTTP protocols, we ensure that the digital entities in the DT application are always in sync with the physical torquing process, allowing for accurate monitoring, analysis, and user interaction.

4. Administration FE: The Administration FE plays a critical role in the management and administration of various operations within the DT application. These operations include establishing connections with the OPC UA server, MQTT broker, and MySQL application, setting up subscriptions with the relevant tags in OPC UA and MQTT, analysing acquired data, handling data presentation and synchronization, and responding to user requests.To ensure the proper execution of these events in the correct sequence, we have employed the Node.js environment as the Administration FE for our DT application. Node.js offers a robust and scalable platform for developing the DT application and managing the flow of operations based on user requests. It enables us to create a server-side application that can

interact with the DT and provide an intuitive user interface for administrators.By utilizing Node.js, we can seamlessly integrate with other technologies and platforms, such as OPC UA, MQTT, and MySQL, to efficiently manage and administer the DT application. Node.js provides a versatile and flexible environment that allows us to handle connections, data analysis, and user interactions effectively.The Administration FE is an essential component in a Digital Twin application as it ensures the smooth operation and management of the DT. It coordinates and orchestrates the various tasks and functionalities, ensuring that they are executed accurately and in the proper sequence. With the use of Node.js, we can harness the power of this environment to develop a robust and efficient Administration FE for our DT application.

Service sub-entity: The service sub-entity in the present case encompasses several functional entities, namely digital modelling, presentation, synchronization, and administration. Let's delve into the details of each of these entities.

1. Analytics FE: The analytics functional entity in this scenario primarily focuses on process control and capability analysis. The following illustrates the calculations behind the working of analytics FE.

   Step 1: Initially the target torque value is determined which is 35 Nm in this case for a certain product and joint in which 5% of deviation is tolerated. Hence the USL = 36.75 Nm and LSL = 33.25 Nm.

   Step 2: Recording the baseline - While recording the baseline data 'Any value above USL or below LSL are rejected and are needed to be recorded again' as the first level of validation is considered. The following 20 data points (Applied torque values) are recorded as baseline (under ideal conditions).

   Baseline = {35.06, 35.05, 34.74, 35.53, 34.24, 34.64, 35.03, 35.73, 34.49, 35.22, 35.19, 36.01, 33.81, 34.85, 33.86, 34.84, 34.41, 35.02, 34.71, 34.72}

   The illustrated histogram (Fig. 6)related to the baseline data points suggests that it follows a normal distribution and thus the following calculations are based on the assumptions of the normal distribution.

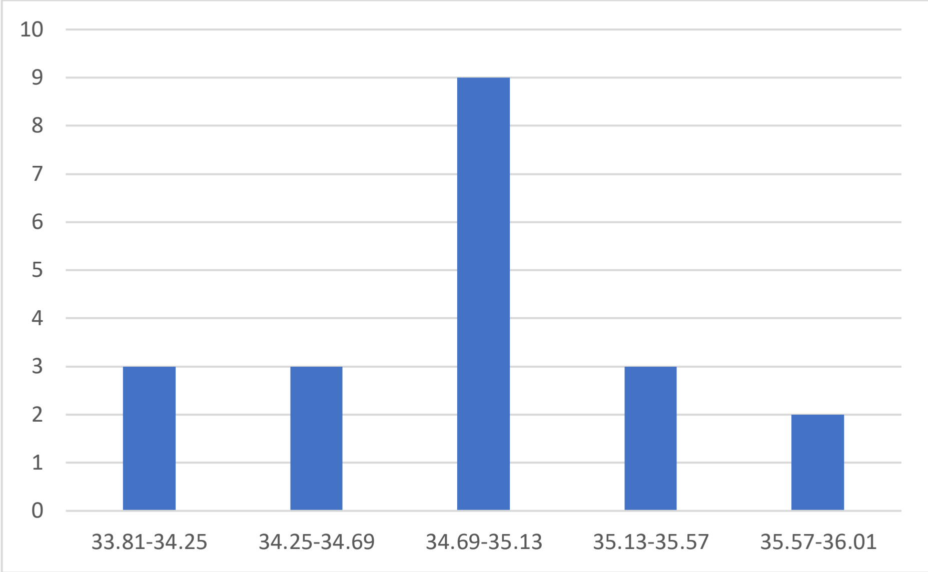


Figure 6:Histogram representing the occurrences of applied torque values in the baseline

Step 3: Calculations related to the R chart - The R chart is used to monitor the process variability at regular intervals in a process. In this case, the difference in the successive applied torque values gives us the moving range.

$$Moving\ Range, R_{i+1} = |X_{i+1} - X_i|$$

Therefore, the moving range corresponding to the applied torque values and the formulated R-chart is illustrated in Fig. 7.

Datapoint	Moving Range
1	
2	0.01
3	0.31
4	0.79
5	1.29
6	0.4
7	0.39
8	0.7
9	1.24
10	0.73
11	0.03
12	0.82
13	2.2
14	1.04
15	0.99
16	0.98
17	0.43
18	0.61
19	0.31
20	0.01

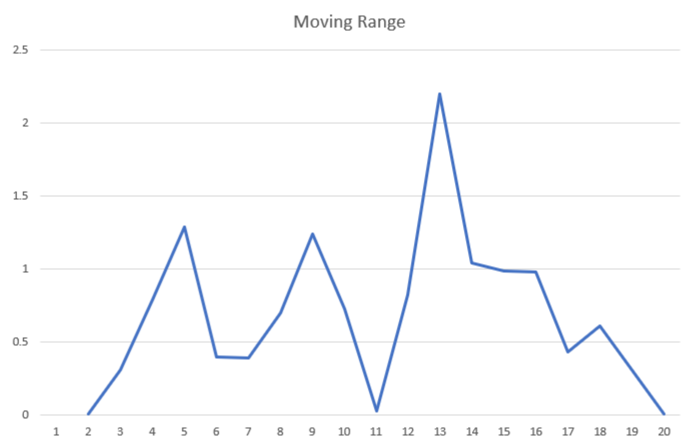


Figure 7: R-chart related to the process

From the available data, we can calculate the average moving range which is used in further calculations

$$Average\ moving\ range, \bar{R} = \frac{\sum R}{N-1} = 0.6989$$

Step 4: Calculation of X chart and control limits - The company requirements were to monitor the process using an X chart with green, yellow, and red zones which illustrate the quality of the process. The green, yellow, and red represent the 1-σ, 2-σ, and 3-σ control limits respectively. The formula for calculating the n-σ control limits is:

$$UCL_x = \bar{X} + n * \overline{\frac{R}{1.128}}$$

$$LCL_x = \bar{X} - n * \overline{\frac{R}{1.128}}$$

Using these equations, the control limits for 1-σ, 2-σ, and 3-σ control limits are (34.2335, 35.4795), (33.6204, 36.0945), and (32.9984, 36.7166) respectively.

Step 5: Calculation of KPIs like C_p, C_{pk} values [47]–

$$Standard\ deviation, \sigma = \frac{\bar{R}}{d2} = \frac{0.6989}{1.128} = 0.6196$$

Where d2 is a control chart constant that depends on the subgroup size, for n=2, d2=1.128

$$Process\ capability\ ratio, C_p = \frac{USL - LSL}{6 * \sigma} = \frac{36.75 - 33.25}{6 * 0.6196} = 0.9415$$

$$C_{pu} = \frac{USL - \bar{X}}{3 * \sigma} = 1.0181$$

$$C_{pl} = \frac{\bar{X} - LSL}{3 * \sigma} = 0.8648$$

$$Process\ capability\ index, C_{pk} = Min(C_{pu}, C_{pl}) = 0.8648$$

Step 6: Generating user recommendations – The following Fig. 8 based on the WECO rules [48] illustrates the criteria for generating the user recommendations.

Recommendation based on Cp/Cpk of base line data	
Cpk	Recommendation
<<1	(1) Process not capable (Raise Alarm) (2) Reduce process variance, (3) Review specification limits, (4) Change of process may be required, (5) If Cpu<Cpl, process mean needs to be shifted towards left (6) If Cpl<Cpu, process mean needs to be shifted towards right
=1	(1) Process is just capable, (Raise Alarm) (2) Reduce process variance, (3) If Cpu<Cpl, process mean needs to be shifted towards left (4) If Cpl<Cpu, process mean needs to be shifted towards right
1-1.33	(1) Process is capable, (2) Reduce process variance, (3) If Cpu<Cpl, process mean needs to be shifted towards left (4) If Cpl<Cpu, process mean needs to be shifted towards right
1.33-2	(1) Process is capable, (2) Reduce process variance if economical (3) If Cpu<Cpl, process mean needs to be shifted towards left (4) If Cpl<Cpu, process mean needs to be shifted towards right
>>2	(1) Process is capable, (2) May reduce control (3) See if the specification limits can be relaxed (4) If Cpu<Cpl, process mean can be shifted towards left, if economical (5) If Cpl<Cpu, process mean can be shifted towards right, if economical

Figure 8: Criteria for generating user recommendations

2. Simulation FE: The simulation FE is responsible for simulating the operations that take place in the OMEs. In our case, we have utilized 3D models to visually simulate the torquing process within the web application, incorporating real-time information such as selected torque, applied torque, and user recommendations related to the process, as depicted in Fig. 9. This FE is crucial in providing an accurate and realistic representation of the process, enabling the identification of potential issues and facilitating process improvement.To generate the 3D models, we have employed the Unity game engine, which offers a robust and flexible platform for creating immersive 3D models and simulations. These models are stored within the Digital Twin application itself and can be accessed and visualized through both the web and AR applications. The simulation functionality provides users with a comprehensive 3D view of the torquing process, allowing them to identify potential issues and make informed decisions regarding process optimization and enhancement.

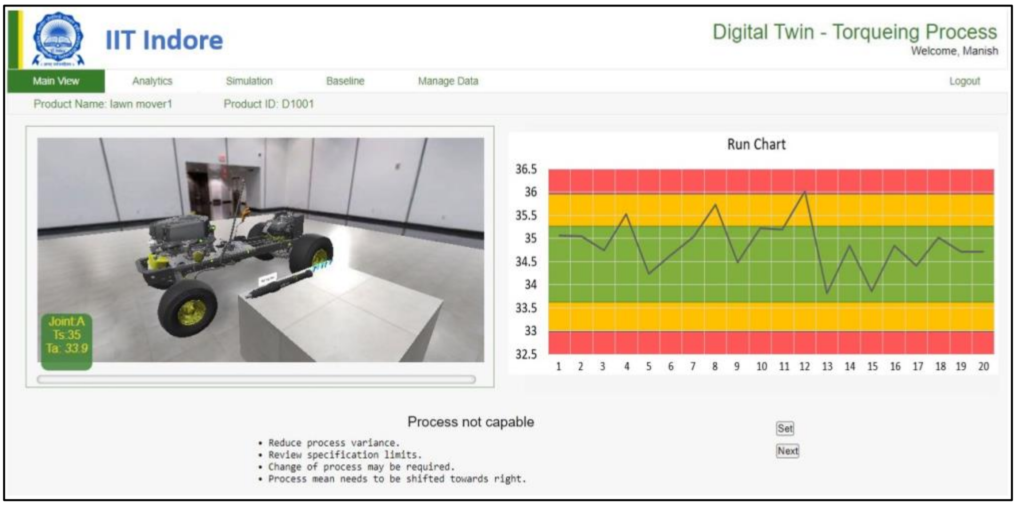


Figure 9: Web applications developed as users of DT

3. Reporting FE: The Reporting functional entity (FE) is responsible for generating comprehensive and customized reports regarding the production process, working in conjunction with the Analytics FE. The results obtained from the analytics activities are stored in the MySQL database application. These results serve as the basis for generating reports tailored to meet the specific requirements of the users.The stored results in the database encompass crucial information such as the completion time of the process, the product ID, the joint ID associated with that particular process, and KPIs including C_p and C_{pk} values. Additionally, the applied torque value, selected torque value, and user recommendations for the process are also included in the stored data.Using this data, the Reporting FE generates detailed reports that provide insights into the production process. These reports can be customized according to the specific needs and preferences of the users, ensuring that the relevant information is presented in a clear and organized manner. The reports serve as valuable resources for monitoring and analysing the performance of the production process, facilitating informed decision-making and process optimization.

Resource access sub-entity: The service sub-entity in the present case consists of access control FE.

1. Access Control FE: The Access Control FE grants access to verified users in the DT application, including the MES, web, and AR applications. Operator login verification is implemented to restrict access to specific

functionalities, ensuring only authorized personnel can utilize them. This safeguard protects the DT application's data and functionalities from unauthorized access and modifications.

Summary:

This chapter focuses on the practical implementation of a DT for quality control in the torquing process of joints. It highlights the significance of digital representations and their role in enhancing accuracy and reliability. The chapter discusses the importance and implementation of various sub-entities and functional entities involved in the DT application, emphasizing their contributions to overall effectiveness and efficiency. The use of web and AR applications is explored, providing users with a comprehensive 3D view of the torquing process and valuable analytics. The use of standardized DT creation process proposed in earlier section offers benefits such as generating user recommendations to control the process, precise digital representations, and enhanced monitoring and analysis capabilities. Fig. 10summarizes the case study by mapping the entire implementation with the proposed DT creation process.

Scope Identification	Details
Understanding the problem statement	Variation in applied and designed torque in the torqueing process in an automotive industry in India
Identifying the physical object	Torquing process
Identifying the Functionalities required	Visualization, Analysis of the observed variation, Generating user recommendation to control the process
Identifying the data required	Static information: Product ID and Joint ID, Dynamic information: Variation in applied and designed torque

System Analysis	Details
Analysis of the operations	Static information from MES application, Dynamic information from torquing tool
Analysis for the communication	Static information from MES application using MQTT, Dynamic information from the torquing tool using OPC UA, DT and database application using MySQL protocol, DT and users using HTTP and websockets

Digital Development	Details
Selecting the DT architecture	DT architecture for quality control in torquing process of joints based on ISO 23247 functional reference architecture [39]
DT modelling	Modelling the FEs: Presentation FE, Digital modelling FE, Synchronization FE, etc.

Figure 10: DT creation in case study 1 mapped with the proposed process

Further, Fig. 11 maps the DT architecture for quality control in torquing process of joints with the file structure of the developed DT. This provides a better understanding related to the implementation of the developed modules with the DT.

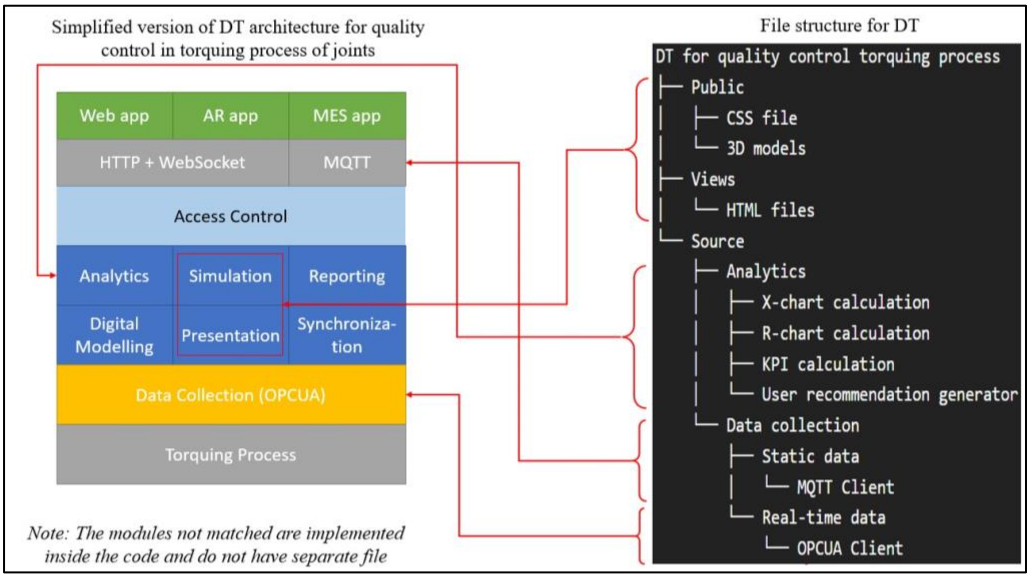


Figure 11: DT architecture for torquing process mapped with the file structure

Chapter 5

Case Study 2 – DT for collaboration in manufacturing

This chapter introduces the second case study of the thesis, which focuses on the implementation of DTs for a machining setups in a laboratory environment to enable collaborative production. This case study serves multiple purposes, starting with the validation of the proposed DT creation process. By applying the standardized process to build the DTs, the case study confirms the effectiveness and practicality of the proposed approach.In addition this, the case study brings a new dimension to the thesis by exploring collaboration using DTs. It demonstrates how DTs can facilitate collaboration in a machining setup by incorporating modules for dynamic event detection, demand sensing, and collaborative decision-making.Furthermore, this case study contributes to the existing body of literature by providing a simple yet comprehensive real-life implementation of collaboration using DTs. By showcasing the successful utilization of DTs for collaborative production, it expands the understanding and application of DTs in the manufacturing domain. Overall, this case study adds valuable insights and practical examples to the existing literature on DT implementation and collaborative production.

The problem addressed in this case study revolves around the need for efficient collaboration among manufacturing elements to minimize the impact of failures and improve overall system efficiency. Failure in the machining setup can result in reduced productivity and operational disruptions. Therefore, it is crucial for manufacturing systems to possess the capability to identify and anticipate potential disturbances or failures in the machines, enabling proactive actions to be taken.

In a network of interconnected manufacturing elements, it becomes essential for the systems to collaborate effectively to predict failures or mitigate the adverse effects of failures on the entire production process. Within this context, two DTs representing distinct manufacturing elements, as discussed in the previous section, are utilized. The primary objective is to demonstrate collaborative production between these two stations using the proposed architecture. This involves the seamless exchange of information and collaboration between the manufacturing systems.

5.1 Scope of collaboration

Understanding the requirements of this case study, the two-stationmachining setup is the physical object in this case, to add functionalities such as workload transfer, workload sharing, and information sharing.

Workload transfer: In this type of collaboration, the architecture enables the complete transfer of workload between different manufacturing systems. When a production order or disturbance occurs, the DTs analyze the demand and capabilities of the systems involved. Based on this analysis, the architecture determines if the workload can be efficiently transferred from one system to another. This type of collaboration allows for the seamless transfer of production tasks, ensuring optimal utilization of resources and enhancing overall production efficiency.

Workload sharing: Collaboration through workload sharing involves the distribution of production tasks among multiple manufacturing systems. The architecture assesses the production requirements and capabilities of the systems to identify opportunities for workload sharing. By dividing the tasks, each system can contribute its specific capabilities, leading to increased productivity and reduced production time. Workload sharing promotes resource optimization and provides flexibility in adapting to varying production demands.

Information sharing: The architecture also facilitates collaboration through the sharing of information among the manufacturing systems. Information sharing involves the exchange of relevant data, such as real-time production status, quality metrics, process parameters, health status, past failure records, etc. This sharing of information enables better coordination and decision-making across the systems. By having access to accurate and up-to-date information, manufacturing systems can synchronize their operations, anticipate potential issues, and collectively work towards achieving production goals.

To achieve these objectives, the DTs need to possess capabilities like dynamic event detection with demand sensing and identifying similar machines.

Additionally, the DTs should be able to generate appropriate collaboration requests, handle responses, and provide control. To enable the functionalities, data related to the setups are required, including information for calculating similarity and real-time data from the setups.

5.2 System Analysis

5.2.1 Analysing the manufacturing systems

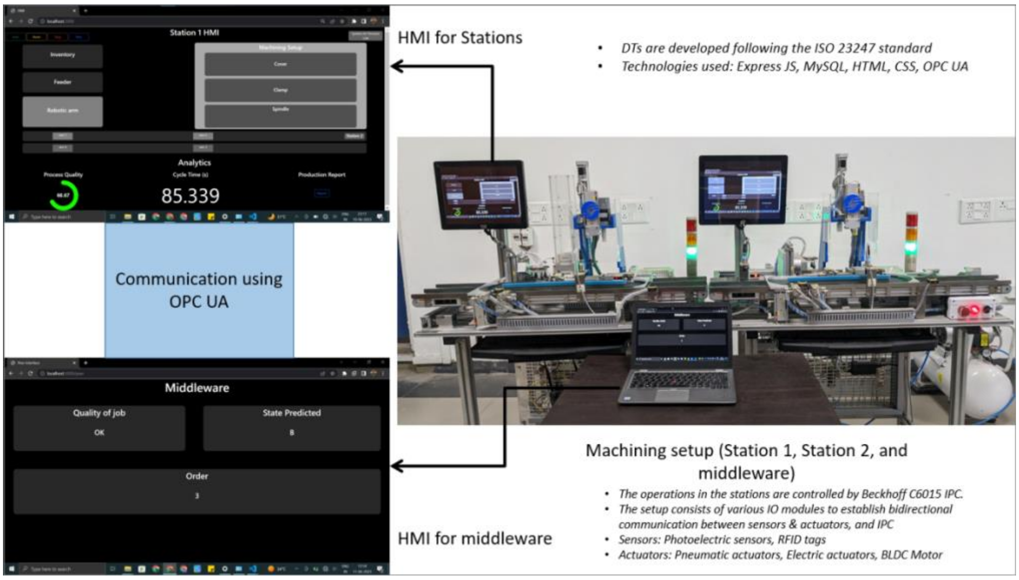


Figure 12: Experimental setup with DTs and middleware

The experimental setup used in this case study consists of a two-station machining setup (Fig. 12), which is a laboratory-scaled version of production lines. Each station within the setup encompasses key components such as inventory, feeder systems, machining setups, and conveyor belts. The setup operates as a pneumatic system controlled by a Beckhoff C6015 Industrial PC (IPC). This IPC serves as the central control unit for managing and customizing the operations of the stations. The pneumatic system allows for flexibility and adaptability in simulating various manufacturing processes. The stations are integrated with industry-grade sensors and actuators which assist in data collection and controlling the system respectively. The presence of conveyor belts facilitates the transfer of jobs or workpieces between the two stations, enabling the demonstration of collaborative production. Although the stations may appear similar in structure, there are inherent structural and operational dissimilarities that mimic real-world manufacturing scenarios.

The static data presented in Table 4 provides insights into the efficiency and economy of production between the two machining setups. Station 1 is identified as the primary system, exhibiting higher efficiency, while Station 2 is considered an auxiliary system that supports Station 1 during exceptional circumstances.

Table 4: Static data related to the stations

Parameters	Station 1	Station 2
Cycle time	61 seconds	85 seconds
Machine time	8 seconds	8 seconds
Setup time	17 seconds	30 seconds
Energy consumption	3.5 KWs	5 KWs
Available historical data	60 datapoints	34 datapoints
Tool age	82 cycles	34 cycles

Realistic parameters have been incorporated to enhance the authenticity of the case while considering the need for simplicity in problem-solving, certain assumptions and information related to the working of stations are given below:

1. Single Job Type: The machining setups involved in the case study are assumed to produce a single type of job. This allows for focused analysis and collaboration within the given context.
2. Customer Order: The order received from the customer is simplified to represent the number of jobs to be produced. This simplification enables a clear understanding of the production requirements.
3. Station Capabilities: Each station in the manufacturing systems is capable of independently producing the job as well as collaborating with other stations. Stations can produce one job at a time. Three types of orders can be executed in station order 1 where the job is produced autonomously by station 1, order 2 where the job is produced by station 2, and order 3 where the job is produced by both station 1 and station 2 in collaboration.
4. DT Capabilities: The presented DTs have been integrated with additional capabilities such as dynamic event detection, demand sensing, identifying similar machines, generating collaboration requests, and managing response and control.

5.2.2 Intermachine communication

In to order achieve a collaborative production framework DTs intermachine communication network between DTs is required. This section discusses the implementation of this network using DTs and middleware (Fig. 13). Currently, in case we are only using two manufacturing elements station 1 and station 2.

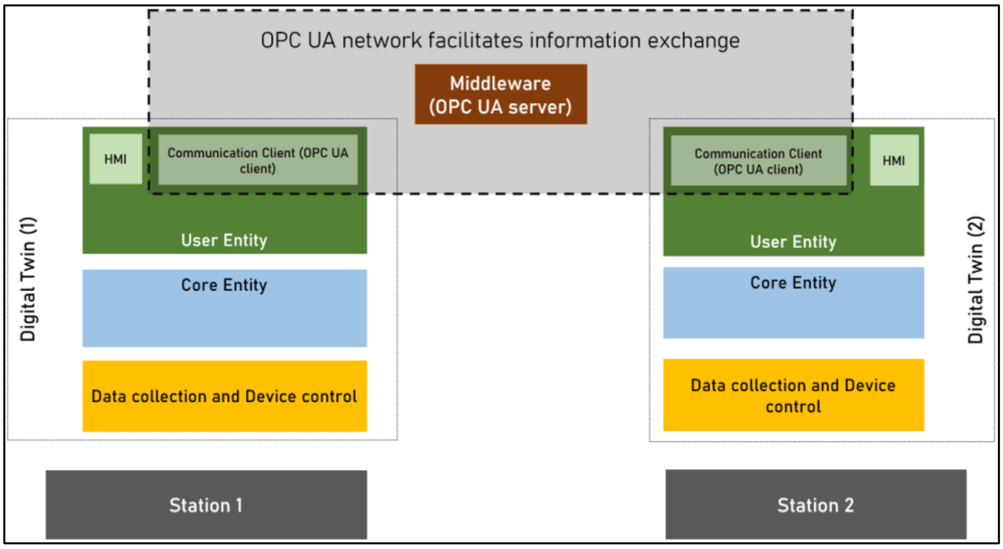


Figure 13: Intermachine communication network using DTs and middleware

The role of middleware in this architecture is played by an OPC UA server that establishes a connection with the communication clients present in the DTs of individual manufacturing elements to facilitate seamless communication between them, eventually implementing collaborative production.

One of the key functionalities of the middleware is to enable the exchange of collaboration requests and responses among the DTs representing these machining setups. This is achieved by utilizing JSON objects, where one of the attributes represents the particular DT in the network of DTs to which the message is to be communicated. The middleware interprets this attribute to ensure secure information exchange between the DTs. The middleware thus provides a secure platform where the response-generating capability of DTs can be utilized to develop closed-loop collaboration applications.

To establish the communication network, the communication clients and middleware are created within the DTs using the documentation available in [38].

5.3 DT development

5.3.1 DT architecture

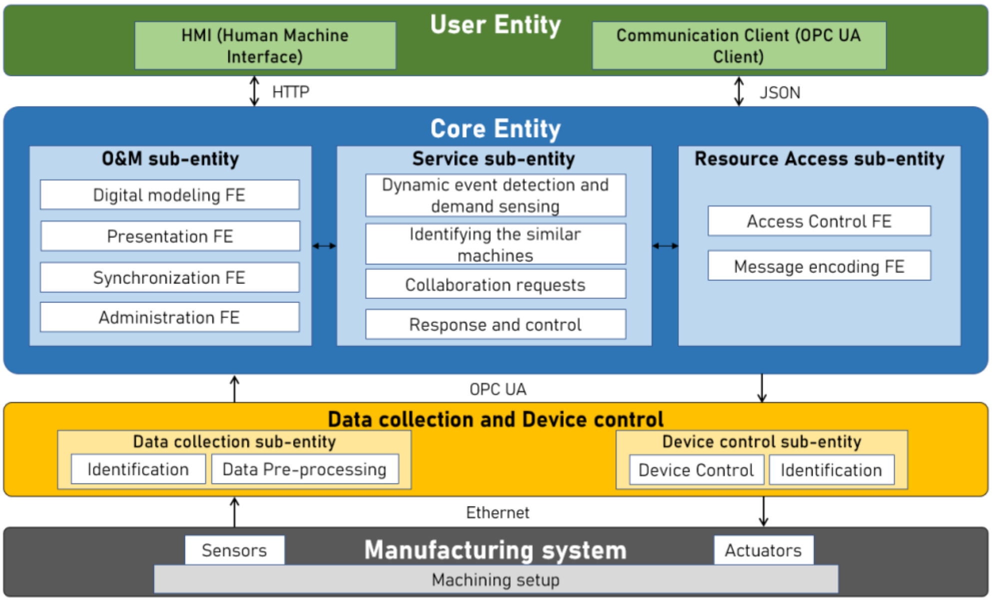


Figure 14: DT architecture of stations for collaborative production

The DT architecture of stations used for collaborative production is presented in Fig. 14. It consists of various specific capabilities likedynamic event detection, demand sensing, identifying similar machines, generating collaboration requests, and managing response and control.These capabilities are discussed in detail to highlight their significance in the upcoming section. However, primary capabilities like digital modeling, synchronization, presentation, and administration are not extensively discussed to maintain the conciseness of the case study. Readers may refer to the previous chapter as well as ISO 23247 for details on these capabilities [34].

5.3.2 Modules involved in Collaboration

In this section, we discuss the significance, implementation, and working of the specific modules required for collaboration.

Dynamic event detection and demand sensing: To enable dynamic event detection, a dedicated module is integrated into the DTs of the manufacturing systems. This module analyzes the demand received from the customer through the HMI present in the user entity of the DT. The demand sensing module processes the order and determines the number of jobs to be produced, subsequently calculating the number of cycles required to complete the order.

In the presented case study, the customer has placed an order for 10 jobs, which would require 10 cycles of machining, whether performed autonomously or in collaboration. This requirement is then forwarded to the dynamic event detection module which operates in two ways. Firstly, it identifies the number of cycles that can be produced autonomously on Station 1 based on the received order. Secondly, it predicts the number of cycles that require assistance from Station 2.

In the working of Station 1, three states are considered: State A, State B, and State C. State A represents a healthy state where Station 1 can complete the entire cycle on its own. State B represents an unhealthy state where Station 1 requires assistance from Station 2 to complete the cycle. State C represents a failed state where Station 1 is unable to continue production.

To predict the occurrence of these states, the Markov approach is employed. The Markov approach relies on historical data related to the occurrence of these states, which is recorded and stored in the DT application. The historical data is stored in a string data type, capturing the sequence of states observed over time. By analyzing the historical data, the Markov approach can estimate the probabilities of transitioning from one state to another. These transition probabilities help in predicting the future state of Station 1 based on its current state and the occurrence of certain events or disturbances. This enables proactive decision-making and facilitates collaboration between the manufacturing stations to ensure smooth production and minimize the impact of failures or disruptions.

Historical data related to states of station 1 = {A, A, A, B, A, C, A, A, A, B, B, A, A, C, A, A, A, B, C, A, A, B, A, B, A, A, C, A, A, A, C, B, A, C, A, A, A, B, B, A, A, A, A, C, A, A, B, A, A, C, A, A, C, B, A, A, C, A, A, B}

$$\begin{array}{c|c} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{pmatrix} 21 & 8 & 9 \\ 8 & 2 & 1 \\ 8 & 2 & 0 \end{pmatrix} \end{array} \quad \cdots\cdots\cdots (1)$$

Matrix representing the number of transitions from one state to another in historical data

$$\begin{array}{c|c} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{pmatrix} \frac{21}{21+8+9} & \frac{8}{21+8+9} & \frac{9}{21+8+9} \\ \frac{8}{8+2+1} & \frac{2}{8+2+1} & \frac{1}{8+2+1} \\ \frac{8}{8+2+0} & \frac{2}{8+2+0} & \frac{0}{8+2+0} \end{pmatrix} \end{array} \Rightarrow \begin{array}{c|c} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{pmatrix} 0.553 & 0.211 & 0.236 \\ 0.727 & 0.181 & 0.092 \\ 0.8 & 0.2 & 0 \end{pmatrix} \end{array} \quad \cdots\cdots (2)$$

Matrix representing the probability of transitioning from one state to another in historical data

Figure 15: Calculating the transition matrix of station 1

Similar to this station 2 also has its own historical data and transition matrix ready for initiating the next cycle.

Historical data related to states of station 1 = {A, A, A, A, A, A, B, B, B, C, A, A, C, B, B, A, A, A, A, C, A, A, C, A, A, B, A, B, A, A, A, A, A, C}

$$\begin{array}{c|c} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{pmatrix} 15 & 3 & 4 \\ 3 & 3 & 1 \\ 3 & 1 & 0 \end{pmatrix} \end{array} \quad \cdots\cdots\cdots (3)$$

Matrix representing the number of transitions from one state to another in historical data

$$\begin{array}{c|c} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{pmatrix} \frac{15}{15+3+4} & \frac{3}{15+3+4} & \frac{4}{15+3+4} \\ \frac{3}{3+3+1} & \frac{3}{3+3+1} & \frac{1}{3+3+1} \\ \frac{3}{3+1+0} & \frac{1}{3+1+0} & \frac{0}{3+1+0} \end{pmatrix} \end{array} \Rightarrow \begin{array}{c|c} & \begin{matrix} A & B & C \end{matrix} \\ \begin{matrix} A \\ B \\ C \end{matrix} & \begin{pmatrix} 0.682 & 0.136 & 0.182 \\ 0.429 & 0.429 & 0.142 \\ 0.75 & 0.25 & 0 \end{pmatrix} \end{array} \quad \cdots\cdots (4)$$

Matrix representing the probability of transitioning from one state to another in historical data

Figure 16: Calculating the transitioning matrix for station 2

The matrix in Fig. 15 (1) and Fig. 16 (3) captures the frequency of transitions from one state to another. To convert these frequencies into transition probabilities, each element in the matrix is divided by the sum of elements in its corresponding row. This transformation yields the transition matrix Fig. 15 (2) and Fig. 16 (4), where the rows represent the current state and the columns represent the next state. Each element in the matrix denotes the probability of transitioning from one state to another. For example, let's assume that the current state is B thus the probability of the next state being C is 0.092. Based on this transition matrix and rules for ensuring efficient production in this case (Table 5), station 1 decides whether to work autonomously (order 1) to complete the next cycle or request station 2 for collaboration.

Table 5: Criteria for decision making

Criteria	Decision
If the probability of the next state being B is > 0.2	Need workload sharing, Order 3 to be executed
If the probability of the next state being C is > 0.2	Need workload transfer, Order 2 to be executed
If the probability of the next state being C is <= 0.2 & the probability of the next state being B is <= 0.2	No collaboration is required, Order 1 is to be executed

Identifying the similarity in machines: While encountering multiple conditions that satisfy the rules presented in Table 5, station 1 faces decision-making challenges due to limited available data. To address this issue, station 1 identifies the presence of another station in the network and employs cosine similarity calculations based on the parameters provided in Table 4 to determine the similarity between the two stations. By leveraging cosine similarity, station 1 quantifies the degree of similarity between itself and station 2 as illustrated in Fig. 17.

Step 1: Representing the stations in the form of vectors

Based on the parameters available in Table 2 following vectors are generated which represent station 1 and station 2:

$\overline{Station1} = 53\,\hat{\imath} + 8\,\hat{\jmath} + 17\,\hat{k} + 3.5\,\hat{l} + 60\,\hat{m} + 82\,\hat{n}$, Station 2 = $110\,\hat{\imath} + 8\,\hat{\jmath} + 30\,\hat{k} + 5\,\hat{l} + 34\,\hat{m} + 34\,\hat{n}$

Step 2: Normalizing the vectors

Unit vector corresponding to station 1, $\overline{s1} = \overline{Station1} \,/\, |\,\overline{Station1}\,|$

$= (53\,\hat{\imath} + 8\,\hat{\jmath} + 17\,\hat{k} + 3.5\,\hat{l} + 60\,\hat{m} + 82\,\hat{n})/\sqrt{53^2 + 8^2 + 17^2 + 3.5^2 + 60^2 + 82^2}$

Unit vector corresponding to station 2, $\overline{s2} = \overline{Station2} \,/\, |\,\overline{Station2}\,|$

$= (110\,\hat{\imath} + 8\,\hat{\jmath} + 30\,\hat{k} + 5\,\hat{l} + 34\,\hat{m} + 34\,\hat{n})/\sqrt{110^2 + 8^2 + 30^2 + 5^2 + 34^2 + 34^2}$

$\Rightarrow \overline{s1} = 0.508\,\hat{\imath} + 0.066\,\hat{\jmath} + 0.142\,\hat{k} + 0.029\,\hat{l} + 0.499\,\hat{m} + 0.683\,\hat{n}$

$\Rightarrow \overline{s2} = 0.828\,\hat{\imath} + 0.078\,\hat{\jmath} + 0.292\,\hat{k} + 0.048\,\hat{l} + 0.331\,\hat{m} + 0.331\,\hat{n}$

Step 3: Dot product

Finally the dot product of these vectors gives us the cosine similarity index between these station

Cosine similarity index = $\overline{s1}\,.\,\overline{s2}$ = 0.86

Cosine similarity varies from -1 to 1. -1 represents perfect dissimilarity, 0 represents no relation and 1 represents perfect similarity

Figure 17: Cosine similarity calculations for station1 and station 2

Collaboration requests: In the case study, collaboration requests play a crucial role in enabling collaborative production between the two stations. These requests are generated based on the calculations and criteria discussed in the previous sections. A dedicated module integrated within the DTs is responsible for generating collaboration requests. Depending on the specific situation, the requests can be categorized into three types: information sharing, workload sharing, and workload transfer.

When the decision-making process in station 1 is hindered due to multiple conditions satisfying the criteria, station 1 generates a collaboration request to initiate information sharing and forwards it to station 2. In response, station 2 provides its transition matrix Fig. 16 (4), derived from its historical data. Considering the calculated similarity, station 1 assigns a weightage to station 2's transition matrix Fig. 16 (4) and combines it with its transition matrix Fig. 15 (2). This amalgamation results in a new transition matrix (Fig. 18) that incorporates collaborative information, enhancing the predictive capabilities of station 1. This request aims to obtain relevant information from station 2 to aid in making decisions related to production.

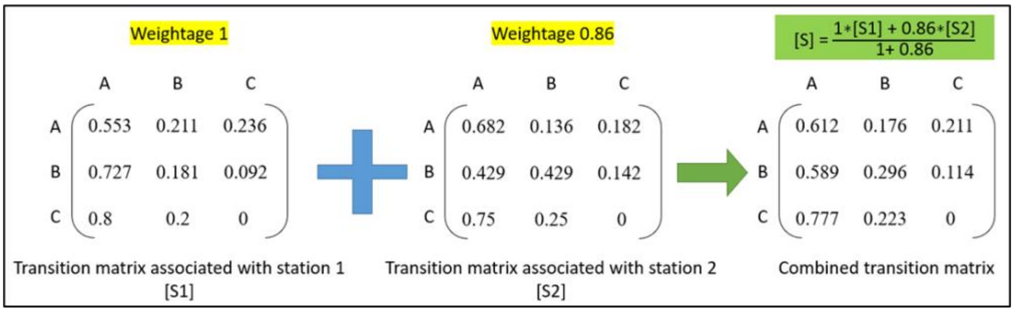


Figure 18: Final transition matrix using information from station 2

Using the updated transition matrix and predefined decision rules, station 1 makes informed decisions regarding collaboration. In cases where uncertainty persists and decision ambiguity remains, priority is given to the more probable state for future occurrences when generating collaboration requests. Similarly, after each cycle, new data points are recorded, and the transition matrices are updated accordingly using the same methodology. This ensures that the transition matrices capture the latest information and reflect the evolving behavior of the machining setups as illustrated in Fig. 19.

Cycle No.	Previous Cycle	Prediction of next state corresponding to previous state	Decision based on Table 5	Information sharing	New Prediction	Final decision	Without Collaboration
1	W (historical data)	[**0.7272**, 0.1818, 0.0909]	A	Not needed	-	A	A
2	A	[0.5526, **0.2105, 0.2368**]	Both parameters satisfy the criteria	Yes	[0.6123, 0.1762, **0.2114**]	C	C
3	C	[0.8, **0.2**, 0]	Parameter on boundary condition	Yes	[0.7768, **0.2231**, 0]	B	A
4	B	[**0.75**, 0.1667, 0.0833]	A	Not needed	-	A	C
5	A	[0.5384, **0.2051, 0.2564**]	Both parameters satisfy the criteria	Yes	[0.6047, 0.1733, **0.2219**]	C	A
6	C	[0.7377, **0.2622**, 0]	B	Not needed	-	B	C
7	B	[**0.7692**, 0.1538, 0.0769]	A	Not needed	-	A	A
8	A	[0.525, **0.2, 0.275**]	Both parameters satisfy the criteria	Yes	[0.5975, 0.1705, **0.2319**]	C	C
9	C	[0.6667, **0.3333**, 0]	B	Not needed	-	B	A
10	B	[**0.7857**, 0.1428, 0.0714]	A	Not needed	-	A	C

Figure 19: Collaborative decision-making in machining setups

In situations where the predicted state of station 1 is state B, indicating that it requires assistance to complete the cycle, a workload-sharing request is generated. This request seeks to distribute the workload between the two stations for improved efficiency i.e., executing the order 3. If a failure is predicted in station 1, a workload transfer request is generated. This request aims to transfer the workload from station 1 to station 2 to ensure uninterrupted production and requests for executing order 2.

These collaboration requests are formulated as JSON objects, with one of the attributes specifying the destination of the request, i.e., station 2. This ensures that the request is directed to the appropriate recipient. To ensure the security and integrity of the collaboration requests, they undergo proper authorization and authentication processes in the access control FE. Once authenticated, the requests are forwarded to the communication clients in the user entity of the DTs for information exchange.

Response and control: In the case study, upon receiving collaboration requests, the DTs perform authentication and authorization checks to ensure the legitimacy of the requests. Once validated, the requests are analyzed to determine the nature of collaboration needed, whether it is related to information sharing, workload sharing, or workload transfer.

In the case of information sharing, if station 1 requests information from station 2, the transition matrix associated with station 2's historical data is communicated back to station 1. This shared information assists station 1 in making informed decisions based on collaborative knowledge. In situations where station 1 requests workload transfer or workload sharing, station 2 generates appropriate control commands to facilitate collaboration. These control commands include starting up station 2 and executing the necessary operations to support the collaboration effectively. In the case of workload transfer order 2 is executed, in the case of workload sharing order 3 is executed.

Additionally, station 2 generates a response indicating its readiness for collaboration. This response informs station 1 whether station 2 is prepared to engage in collaboration based on its current status and workload capacity.

Summary:

This chapter presents a case study on the implementation of DTs for collaboration in manufacturing. The study focuses on a machining setup in a laboratory environment and showcases how DTs can facilitate collaborative production. The case study validates the effectiveness and practicality of the proposed DT creation process by applying a standardized approach to build the

DTs. The DTs incorporate dynamic event detection, demand sensing, and collaborative decision-making modules to enable collaborative production between two stations. The study provides a simple yet comprehensive and practical example for the implementation of DTs for collaboration in the manufacturing domain. The working of modules developed in this case study is presented in the Fig. 20.

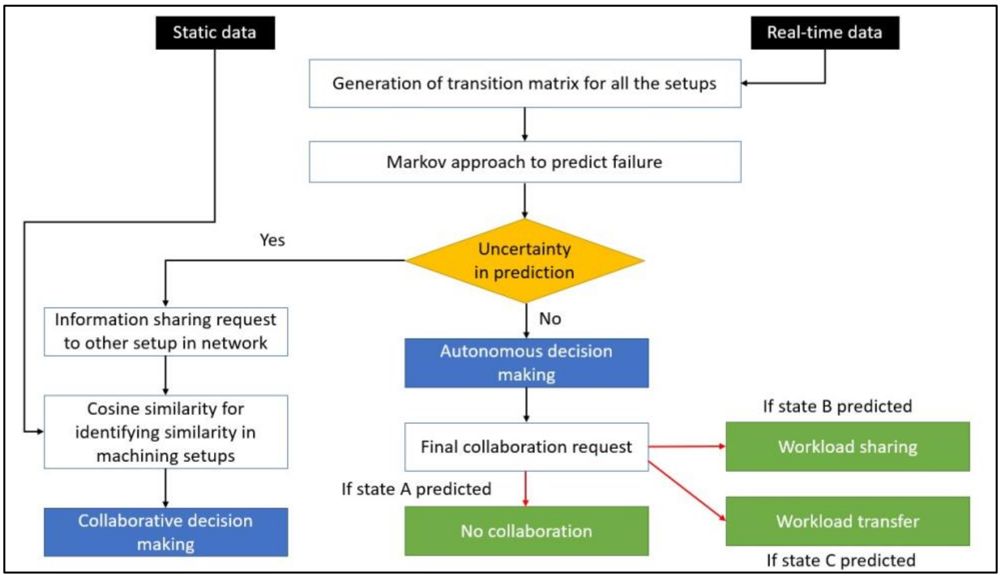
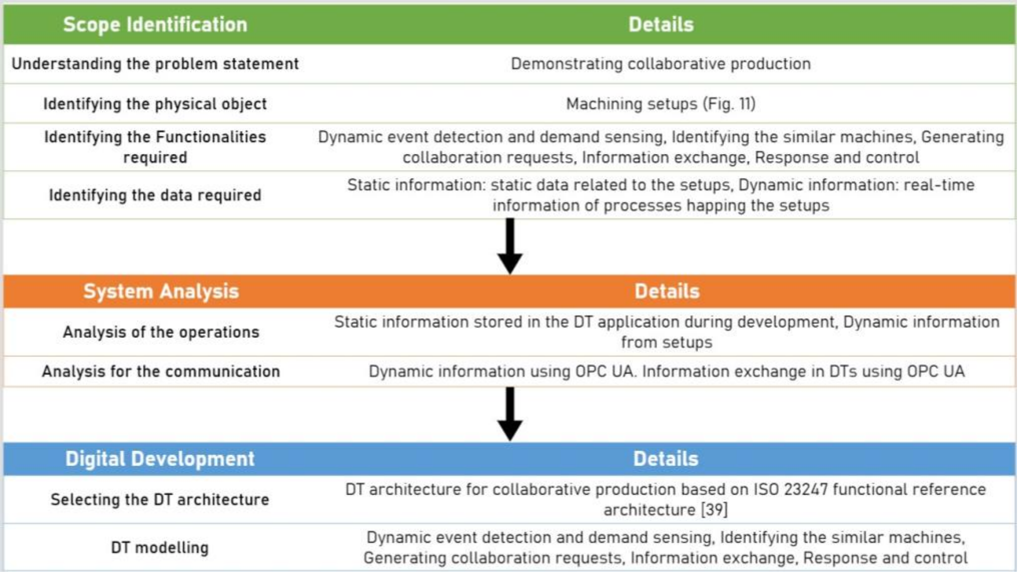


Figure 20: Working of modules in DT for collaboration

Overall, this chapter presents a simple strategy for collaboration in manufacturing elements using DTs and also discusses the creation of these DTs. Fig. 21 summarizes the case study by mapping the entire implementation with the proposed DT creation process.



Scope Identification	Details
Understanding the problem statement	Demonstrating collaborative production
Identifying the physical object	Machining setups (Fig. 11)
Identifying the Functionalities required	Dynamic event detection and demand sensing, Identifying the similar machines, Generating collaboration requests, Information exchange, Response and control
Identifying the data required	Static information: static data related to the setups, Dynamic information: real-time information of processes happing the setups
System Analysis	**Details**
Analysis of the operations	Static information stored in the DT application during development, Dynamic information from setups
Analysis for the communication	Dynamic information using OPC UA. Information exchange in DTs using OPC UA
Digital Development	**Details**
Selecting the DT architecture	DT architecture for collaborative production based on ISO 23247 functional reference architecture [39]
DT modelling	Dynamic event detection and demand sensing, Identifying the similar machines, Generating collaboration requests, Information exchange, Response and control

Figure 21: DT creation in case study 2 mapped with the proposed process

Further, Fig. 22 maps the DT architecture for collaboration in manufacturing elements with the file structure of the developed DT. This provides a better understanding related to the implementation of the developed modules with the DT.

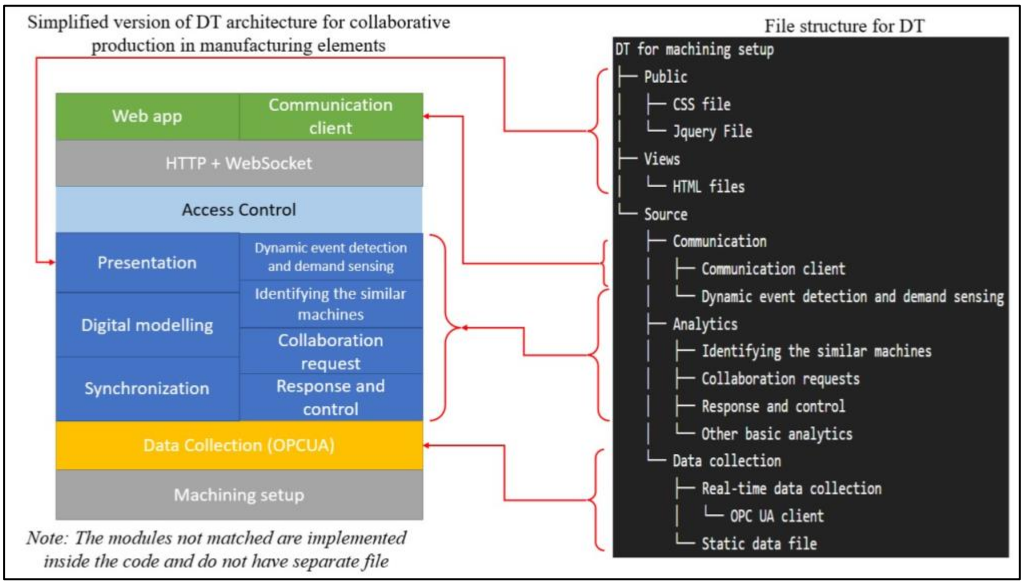


Figure 22: DT architecture for collaboration mapped with the file structure

Chapter 6

Conclusion and Future Work

The thesis work has yielded several significant outcomes in the realm of DTs implementation. One of the key contributions is the identification of critical challenges in the implementation of DTs, particularly the lack of standardization and the scarcity of real-life implementation literature. These challenges pose significant barriers to the widespread adoption of DTs in the manufacturing sector. In response to these challenges, the thesis proposes effective solutions through the development of a standardized DT creation process and the presentation of two comprehensive case studies.

The proposed standardized DT creation process is a pivotal outcome of the thesis. It addresses the lack of standardization in implementing DTs in manufacturing by providing a structured framework that guides developers and practitioners through the entire DT creation journey. By following this standardized process, the inherent complexities and uncertainties in DT implementation can be effectively managed, leading to more efficient and successful outcomes. Another notable outcome of the thesis is the contribution of two compelling case studies that exemplify the implementation process of DTs in the manufacturing domain. These case studies serve as practical examples that bridge the gap in the limited availability of real-life implementation literature.

The two case studies presented in this thesis exemplify the practical implementation process of DTs in the manufacturing domain, bridging the gap in the limited availability of real-life implementation literature. The first case study focuses on quality control in the torquing process of joints, showcasing the integration of various functionalities like analytics, monitoring, visualization, and generating user recommendations for process control. The second case study presents a collaborative production framework for a two-station machining setup, highlighting key functionalities such as dynamic event detection and demand sensing, identifying similar machines, generating collaboration requests, information exchange, and managing response and control.

The case studies not only demonstrate the successful implementation of DTs but also validate the proposed DT creation process. Through the timely identification and mitigation of challenges, the proposed process ensures the streamlined and effective development of DTs in manufacturing. The outcomes of this research contribute to the existing body of literature by providing solutions to key challenges, paving the way for wider adoption and application of DTs in real-world manufacturing scenarios.

While this thesis has achieved significant advancements, there are several avenues for future research to further enhance the field of DT implementation in manufacturing. Three key areas for future work are identified:

First, in scenarios where numerous 3D models with minor design variations are involved, the thesis proposes the creation and storage ofthe 3D models in the DT. However, future research can focus on developing interfaces between DTs and existing 3D engines, allowing the DT to dynamically build 3D models based on actual assembly requirements.

Second, the models employed in the second case study, such as the Markov approach and cosine similarity, may have limitations in real-life industrial scenarios.The repetitive use of the Markov approach can introduce skewness in state predictions, and the cosine similarity model may not comprehensively capture the similarity between two machines. Future research can explore alternative approaches to address these limitations and improve the accuracy and reliability of state predictions and similarity measurements between machines.

Third,the development of DT is a coding-intensive process that involves the use of several additional tools and technologies to ease communication and fulfil the goal of DT. As a result of this constraint, DT generation becomes a skilled activity, increasing the cost and duration of implementation. This restricts the usage of DT to large-scale enterprises. To overcome this problem, researchers may concentrate on building a no-code or low-code tool in which the majority of implementation duties are automated, allowing a person with modest programming abilities to create a DT for his or her application. This will aid in the broader adoption of DT principles in Small and Medium Enterprises (SMEs)

By exploring these areas of future research, we can continue to advance the field of DT implementation in manufacturing, making it more versatile, accurate, and accessible to a wider range of industries and organizations.

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