UNIVERSITY OF WEST ATTICA

SCHOOL OF ENGINEERING

MSc in Oil and Gas Process Systems Engineering

Dissertation

Title:	**Industry 4.0 – Digital Transformation** **ISA 95 Digital Twin**
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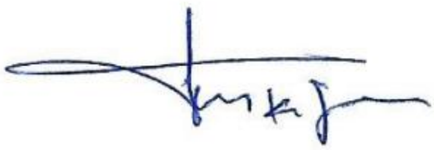

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Παράβαση της ανωτέρω ακαδημαϊκής μου ευθύνης αποτελεί ουσιώδη λόγο για την ανάκληση του πτυχίου μου».

Επιθυμώ την απαγόρευση πρόσβασης στο πλήρες κείμενο της εργασίας μου μέχρι …………………….. και έπειτα από αίτηση μου στη Βιβλιοθήκη και έγκριση του επιβλέποντα καθηγητή.

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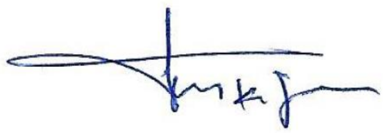

ABSTRACT

The fourth industrial revolution represents a significant advancement in technology, encompassing AI, robotics, IoT, 3D printing, and other innovations. These advancements are driving transformative changes across industries, leading to the emergence of new business models, disruptions to established players, and major shifts in production, consumption, transportation, and delivery systems. To create a shared understanding and direction, it is essential to develop a global vision that recognizes the profound impact of technology on our economic, social, cultural, and human aspects, both now and in the future.

According to Britannica, the industrial revolution refers to the shift from an agrarian and handicraft-based economy to one dominated by industry and machine manufacturing. On the other hand, the fourth industrial revolution is characterized by the adoption of electronics and information technology to facilitate automation in production. It involves enhanced communication and connectivity, the utilization of new technologies, and the automation of manufacturing and industrial processes.

In order to remain competitive and enhance profitability, oil and gas companies must embrace successful digital initiatives to cut costs and improve productivity. The oil and gas industry faces new challenges and opportunities due to geopolitical changes, resource discoveries, climate change, new energy sources, and emerging technologies. To address these trends, the industry needs to integrate and adapt large-scale changes effectively and explore more profitable energy sources. Additionally, there is a growing focus on leveraging information technology to minimize the environmental impact of oil and gas operations and promote sustainability. The Industrial Internet of Things (IIoT), data analytics, big data, cloud computing, mobile applications, wireless networks, social media, and other digital technologies are driving the digital transformation and adding value to the industry's business environment.

Smart refineries play a crucial role in maximizing the value of the entire supply chain in the chemical industry, from crude oil exploration to the production, transportation, storage, refining, and sale of oil products. Both digital refineries and intelligent refineries aim to extract the maximum value from the supply chain. The digital refinery serves as the foundation, utilizing process automation and IT management to enhance

operations. The concept of a smart refinery is further extended with the idea of an intelligent refinery, which leverages extensive knowledge to optimize processes and production even further. The key outcomes of implementing an intelligent refinery include optimal control of production planning, scheduling, and operations; comprehensive lifecycle management and predictive maintenance; optimization of energy consumption throughout the plant; and integrated optimization of sales and logistics processes

The journey towards digital transformation starts with the process of digitization, where physical objects or analog information are converted into their digital counterparts. Digitization serves as the foundational step and holds great significance in the overall process of digital transformation. By utilizing digital technologies and the data derived from digitized processes and interactions, digitization enables the improvement and implementation of various processes, making them more efficient and effective. By leveraging the data generated from digital transformation, companies can become more competitive, improve customer satisfaction, and create new revenue streams.

The ANSI/ISA 95.00.0X series of standards was developed by the International Society of Automation (ISA) with the aim of establishing standardized practices and methods for integration between the enterprise level and the control level. These standards provide a framework for seamless communication and interaction between different systems, allowing for efficient information exchange and coordination between enterprise systems and industrial control systems. The standards promote interoperability and consistency, facilitating the integration of various functions and processes within an organization... The main goal was to solve the problems that came up as automated interfaces between enterprise level and control system level evolved, but also to cut costs and make sure everyone used the same terms, had the same requirements, and had the same specifications.

ISA standard, describes and explain the interface content between enterprise operations, functions, or activities and manufacturing control operations. The main goal is to make interface terminology more uniform and consistent, to reach a high level of common language, and to reduce risks, costs, and other possible mistakes. The main focus is on how enterprise systems and control systems can be linked and work together with a high level of flexibility.

Cutting-edge technology known as "digital twins" is poised to bring significant changes to the oil and gas industry. Digital twins are receiving considerable attention due to their potential benefits. A digital twin refers to a real-time, exact replica or simulation of a process, asset, or project. It is powered by a digital thread, which connects data from various stages of the product lifecycle. This integration of data enables the digital twin to provide valuable insights and analysis. By leveraging digital twins, the oil and gas industry can enhance operational efficiency, optimize asset performance, and make informed decisions based on real-time data.

Digital twins drive oil and gas companies to an advanced level of insight into their operations that has never been seen before. This lets them improve performance, predict and stop problems before they happen, reduce downtime, and keep things running smoothly. Oil and gas operators are now trying to reach their full potential because of the promise of creating value. These assurances cover improved safety, reliability, foresight, and production optimization. With digital twins, oil and gas companies can proactively address potential issues and efficiently manage their operations.

The true value of digital twin technology and its specific benefits can be difficult to measure, and there is a lack of consensus on how to effectively utilize this technology. Standardized reference architectures and measurement frameworks are needed to address these challenges and establish industry-wide standards. This will enable the oil and gas industry to realize the full potential of digital twins and reap their benefits.

Digital twins offer a range of benefits, serving as virtual proxies or autonomous systems, depending on the specific application. A comprehensive digital twin framework incorporates modeling and analytics, enablement technology, and data. In the oil and gas industry, digital twins enable proactive asset management, allowing operators to anticipate and prevent potential issues, thereby reducing unplanned downtime and associated costs. This technology enhances operational efficiency and serves as a valuable asset for oil and gas companies.

Keywords

Industrial Revolution 4.0, Digitalization, Digital Transformation, Standard ISA 95, Digital Twin

ACKNOWLEDGEMENTS

To the people who supported my efforts and believed to me, especially to my family for the time I did not spend with them working this dissertation and to Mr Stefanakis Athanasios, Chemical Engineer, for his valuable help, guidance and insights.

ACKNOWLEDGMENT - Sponsors

I would like to express my gratitude to the *Msc Oil and Gas Process Systems Engineering* sponsors HELLENIC PETROLEUM SA, Aspropyrgos Municipality and the University of West Attica for their funding and continuous support. The attendance and success of this Course would not be possible without their invaluable contribution.

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GLOSSARY OF TERMS AND ACRONYMS

1D:	One Dimensional
2D:	Two Dimensional
3D:	Three Dimensional
5G:	Fifth Generation
AI:	Artificial Intelligence
AD:	Additive Manufacturing
AR:	Augmented Reality
BP:	British Petroleum
CBR:	Cost-Benefit Ratio
CPS:	Cyber-Physical System
CAD:	Computer-Aided Design
CAM:	Computer-Aided Manufacturing
CCTV:	Closed-Circuit Television
CPPS:	Cyber-Physical Production Systems
CSaaS:	Control System as a Service
DML:	Deep Machine Learning
DA:	Data Analytics
DNN:	Deep Neural Network
DT:	Digital Twin
DTP:	Digital Twin Prototype

DTI:	Digital Twin Instance
DTA:	Digital Twin Aggregate
DTE:	Digital Twin Environment
DTS:	Distributed Temperature Sensors
ERP:	Enterprise Resource Planning
IaaS:	Infrastructure as a Service
IoT:	Internet of Things
IIoT:	Industrial Internet of Things
I4.0:	Industry 4.0
IT:	Information Technology
ICT:	Information and Communication Technology
ISO:	International Organization for Standardization
LoRa:	Long Range
LPWA:	Low Power Wide Area
M2M:	Machine-to-Machine
ML:	Machine Learning
MES:	Manufacturing Execution Systems
OT:	Operational Technology
PaaS:	Platform as a Service
SaaS:	Software as a Service
SCADA:	Supervisory Control and Data Acquisition

WSN: Wireless Sensor Network

PHM: Prognostics and Health Management

RFID: Radio Frequency Identification

VR: Virtual Reality

CHAPTER 1

Introduction

1.1 Background and motivation for the work

According to Klaus Schwab of the World Economic Forum, the term "revolution" refers to a significant and rapid change. Throughout history, revolutions have occurred when new technologies and alternative perspectives have led to major transformations in economic systems and social structures. These revolutions have the power to reshape industries, disrupt traditional practices, and bring about significant societal shifts. The Fourth Industrial Revolution, characterized by the convergence of digital, physical, and biological technologies, represents a transformative era with the potential to revolutionize industries and societies worldwide." (Schwab, 2016)

A revolution is transforming how we live, work, and interact. The fourth industrial revolution is unprecedented in scale, scope, and complexity. Many of these ideas are still young, but they are accelerating as they build on each other. The industrial revolution is changing how we work, communicate, express, inform, and entertain ourselves, as well as how governments and institutions operate. New ways of influencing behavior, as well as production and consumption systems, could promote natural environment regeneration and preservation while incurring no additional costs.

It can be inferred that "Industry 4.0," provides a broad framework for the initiation of innovative technologies such as the "Industrial Internet of Things," "big data," "digital twins," and other emerging technological trends. This concept encompasses the integration of physical and digital systems, paving the way for advanced manufacturing processes, automation, data-driven decision-making, and interconnectedness across various industries. The core idea is to leverage these technologies to enhance productivity, efficiency, and overall performance in a rapidly evolving digital landscape.

It was important for the industry, the manufacturers, and the businesses in general to speak the same language and adapt to the new technological trends that were developing quickly in an efficient way.

The ANSI/ISA 95 series was introduced by the International Society of Automation (ISA, 2022) to address the need for a standardized interface between control functions and other enterprise functions, based on the hierarchical form. (Wikipedia, 2023). This series of standards, known as ISA-95, is an internationally recognized standard that facilitates the development of automated interfaces between enterprise systems, applications, and industrial control systems. It is designed to be applicable across various industries and processes, including batch, continuous, and repetitive operations. The ultimate objective of ISA-95 is to allow information to be exchanged between various types of systems, both industrial control systems and enterprise systems, so that they can interact with one another and to provide standard, consistent language. (Monchinski, 2020) and to enable seamless exchange of information between different types of systems, promoting interaction and ensuring a consistent and standardized communication framework The ISA-95 Standard is a globally recognized set of guidelines and standards for manufacturing process automation. (Jimenez, 2021)

ISA 95 standard defines reliable, secure, and cost-effective information exchange. By standardizing data and information flow between hardware, software, and network systems, the ISA-95 Standard reduces the complexity of integration projects, allowing manufacturers to quickly and easily realize a return on their investments. ISA-95 creates an automated environment in which to perform industrial processes with greater efficiency and explain the enterprise model in detail, including how it works to control manufacturing, run businesses, and share information. Establish a common language for describing and fully understanding businesses.

Manufacturing Execution Systems (MES) refers to the electronic information exchange that enables seamless integration between manufacturing control functions and other enterprise functions. It encompasses the definition of data models and exchange standards, allowing for efficient communication and information exchange across different departments within an organization. MES facilitates the coordination of manufacturing processes, business operations, and information exchange, serving as a common language for effective communication and integration of various business functions. (Seibl and Theobald, 2017)

So, in order for the enterprises to adapt to the new technologies, a roadmap was being made and given to them for use.

Currently, digitalization, with a particular emphasis on "digital twins," is significantly transforming the business landscape. Digital twins, which are virtual replicas of physical machines or systems, have become instrumental in various industries for problem identification and productivity enhancement. The rapid advancement of information technologies, including the Internet of Things (IoT), cloud computing, big data analytics, and artificial intelligence (AI), is accelerating the digitization process. This convergence of the real and virtual realms is driving innovation across all sectors, making digitalization a key catalyst for progress. The adoption of digital solutions is not limited to the oil and gas industry alone. Various industries are recognizing the significance of digital technologies, including the timely relevance of "digital twins." Recent references indicate the widespread implementation of digital technologies across sectors. Industries are leveraging these technologies to achieve operational efficiencies, gain deeper insights into value chains and product lifecycles, enhance customer satisfaction, improve reliability, and optimize information management. The broad application of digital solutions reflects the growing recognition of their transformative potential across diverse sectors.(Elijah et al., 2021)

The digital twin (DT) is an increasingly popular approach for businesses to integrate physical and digital systems. It involves the seamless combination of a physical asset or entity with its digital representation, allowing for bidirectional communication, collaboration, and evolution. Through various digitization technologies, the entities, behaviors, and relationships of the physical world are captured and transformed into high-fidelity virtual models. These virtual models are enriched with real-time data from the physical world, ensuring their accuracy and fidelity in reflecting the corresponding physical entities. The digital twin concept enables businesses to create dynamic and comprehensive representations of their assets, facilitating better understanding, analysis, and optimization of their operations.

The perception of digital twin technology can vary depending on the perspective of the individuals involved. Process controls and operations professionals may view digital twin technology as an extension of existing process control practices, focusing on improving operational efficiency and performance. They may see it as an evolution rather than a completely new concept.

On the other hand, IT departments in energy companies may view digital twins as a distinct and innovative approach due to the integration of emerging technologies such as IoT sensors, cloud computing, and advanced data management. These technologies enable real-time data collection, analysis, and visualization, allowing for more comprehensive and detailed digital representations of physical assets.

Both perspectives have validity, as digital twin technology builds upon established process control principles while leveraging new technologies to enhance its capabilities. Ultimately, digital twins provide a more holistic and data-driven approach to asset management, enabling better insights, decision-making, and optimization across various industries, including the energy sector.

The motivation behind this work is driven by the need to explore and comprehend the practical implementation of Digital Twin technology in enhancing products and processes, ultimately leading to autonomous operations. To successfully implement a digital twin system, it is crucial to follow a systematic approach encompassing its design, construction, operation, maintenance, and continuous improvement.

However, several challenges arise during the implementation of digital twins, one of which is achieving a consistent understanding of the concept across different fields and perspectives. Digital Twin technology is multidisciplinary in nature, and ensuring a shared understanding and collaboration between various stakeholders becomes essential to leverage its full potential.

Addressing these challenges and gaining a comprehensive understanding of Digital Twin technology can pave the way for its successful adoption and utilization in diverse industries, enabling improved performance, efficiency, and autonomous operations.

1.2 Aims, Objectives and Scope of the Work

In summary, this thesis aims to explore the relationship between Industry 4.0 and the digital transformation of enterprises, with a specific focus on the implementation of the ANSI/ISA 95 series standards. It also investigates the concept of digital twin technology and its potential applications in the Smart Manufacturing and Oil and Gas sectors. The goal is to provide insights into how digital twin technology can contribute to the advancement of these industries in the context of Industry 4.0.

1.3 Work Summary

Chapter 1	Introduction
Chapter 2	Industrial Revolution 4 and Digital Transformation.
Chapter 3	ISA 95 Enterprise-Control System Integration Suite of Standards
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CHAPTER 2:

Industrial Revolution 4 and Digital Transformation

The rapid advancement and convergence of technologies such as Artificial Intelligence, robotics, IoT, and quantum computing are reaching a crucial turning point. As these technologies continue to mature and interact with each other, they create a powerful synergy that can drive transformative changes. These innovations have the potential to reshape various industries and transform the way we live and work. As billions of people become connected through mobile and other devices, unprecedented processing power and knowledge access are becoming available and easier. The fusion of technologies across different domains is creating new possibilities and opportunities. While the exact impact and timeline of this revolution are uncertain, it is clear that we are on the brink of significant changes that will shape the future.(Koslowski, 2014; Schwab, 2016)

New business models, incumbent disruptions, (Christensen et al., 2015) and production, consumption, transportation, and delivery system changes are happening across all industries. Work, communication, expression, and entertainment are changing in society. Governments, institutions, education, healthcare, and transportation are all changing. Technology can help regenerate and preserve natural habitats instead of causing externalities. The changes are massive, rapid, and unique.

The complex nature and interconnectivity of emerging technologies mean that all interested parties in the globalized world, business, academia, and nongovernmental organizations work together just to better understand the future trends. To build a common vision with shared goals and values, we need shared understanding. We need a global vision of how technology is redefining our economic, social, cultural, and human context and subsequently influencing not only our present lives but also those of future generations.(Schwab, 2016; Stearns, 2020)

The term "revolution" characterizes a sudden and profound transformation. Throughout history, revolutions have occurred when novel technologies and innovative perspectives have instigated significant shifts in social and economic frameworks.

Drawing from historical context, it is important to recognize that the full impact of these changes may take years to materialize.(De Vries, 1994; Schwab, 2016)

The term "Industrial Revolution" carries certain limitations when used as a historical term. To provide a broader historical context, a new concept called the "industrial revolution" has been introduced. This concept takes into account the reallocation of resources, which resulted in an increase in both labor and commodity supplies in the market, as well as a rise in demand for the goods produced. It acknowledges that the Industrial Revolution was not solely a supply-side phenomenon, but also involved significant demand-side characteristics at the household level. This understanding has implications for the economic history of the 19th and 20th centuries. (De Vries, 1994; Schwab, 2016; Simio, 2023; Zaleng, 2022)

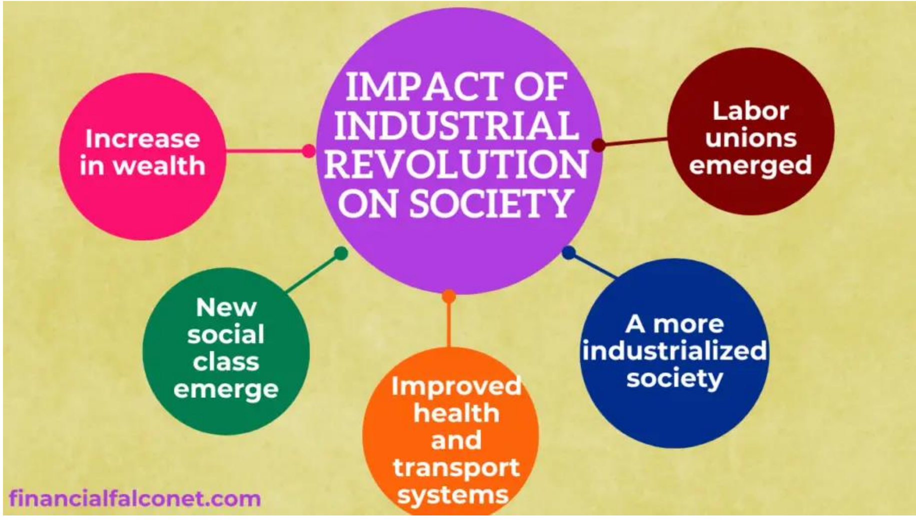

Figure 1. How did the industrial revolution change society? (Zaleng, 2022)

Our investigation aims to explore the transformative impact of the Industrial Revolution on world history. We will examine the international factors that contributed to its emergence, its widespread diffusion across the globe, and its ongoing effects from the late 18th century until the present day. Scholars such as Stearns (2020) and Zaleng (2022) have recognized the Industrial Revolution as the most significant change in human history over the past three centuries. Its influence continues to shape the modern world. (Stearns, 2020; Zaleng, 2022).

Definition of Industrial Revolution 4.0

The industrial revolution, spanning the last three centuries, stands as the most remarkable and impactful development in human history. Its influence continues to shape the modern world. From its inception, the industrial revolution had a global reach, characterized by transformative changes to international economic relations. These modifications not only redefined the global economy at the time but also continue to shape and redefine it in the present day. (Marr, 2018; Stearns, 2020; Zaleng, 2022)

All of the great industrial revolutions were caused by the discovery and adoption of new technologies, methods, and ideas. These changes had an effect on both the economy and the technology of the time. They created a new culture in the technological field of each era and changed the way people organized themselves socially and got along with each other.

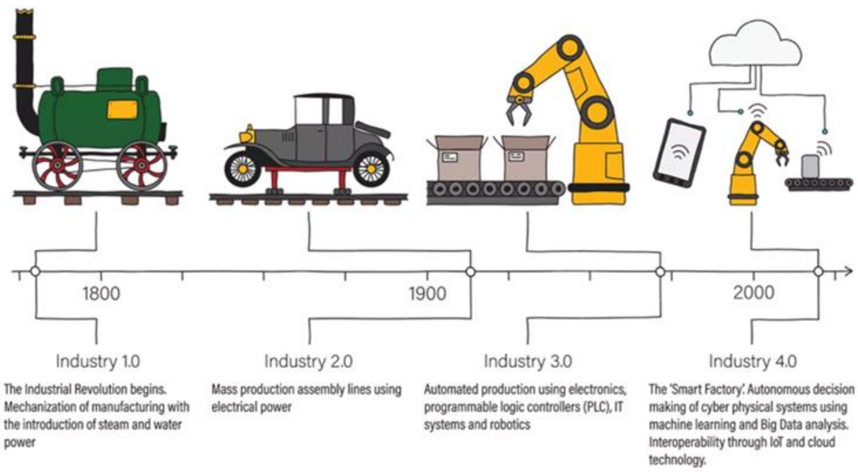

Figure 2. Industrial Revolutions stages through ages.(Simio.)

According to Britannica, the term "industrial revolution" refers to the transition from an agrarian and handicraft-based economy to one that is primarily driven by industry and machine manufacturing. It signifies a significant shift in economic structure and production methods (Britannica.)

First Industrial Revolution (mechanization).

The First Industrial Revolution, also known as the mechanization period, started in the 18th century. It was marked by a shift from manual production methods to mechanized processes. Key developments during this time included the adoption of steam power for industrial use and the emergence of mechanized factory systems. These advancements revolutionized production and set the stage for further industrial transformations in the future. (Marr, 2018; Stearns, 2020; Zaleng, 2022)

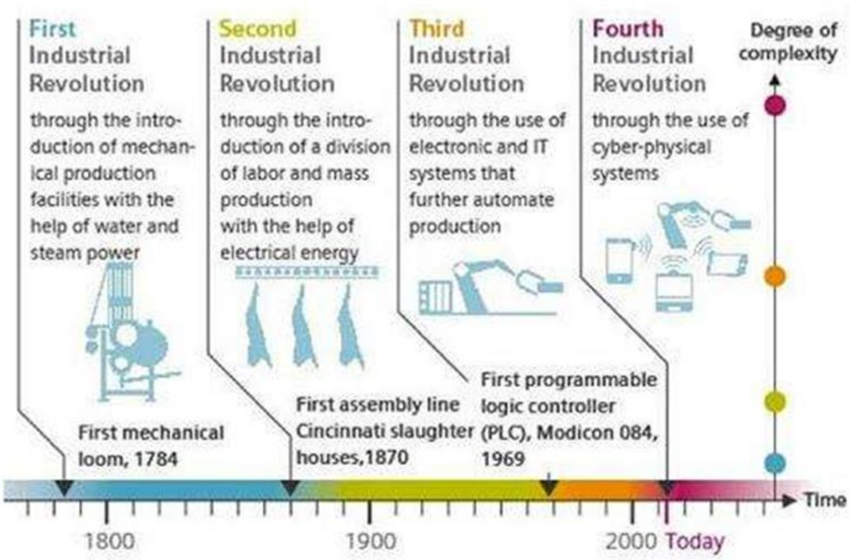

Figure 3. From Industry 1.0 to 4.0. Timeline and Roadmap. (Mathas, 2013)

The Second Industrial Revolution (mass production).

The Second Industrial Revolution, also known as the era of mass production, commenced in the 19th century It is distinguished by the extensive use of electricity for industrial purposes as well as the evolution of changes in factory systems to accommodate new modern and assembly production lines. Henry Ford (1863–1947) adapted a mass production system in automobile production, changing the process of assembly, which reflected higher productivity rates and lower costs. (Marr, 2018; Stearns, 2020; Zaleng, 2022)

The Third Industrial Revolution (also known as the Digital Revolution)

The Third Industrial Revolution, often referred to as the Digital Revolution, marks the era of electronics and information technology being leveraged in order to enable automation in production more automated systems in the manufacturing process with less human input and intervention. higher productivity rates and lower costs. It builds solid foundations for the next technological wave. (Marr, 2018; Stearns, 2020; Zaleng, 2022)

Industry 4.0 is the fourth industrial revolution.

Industry 4.0, also known as the fourth industrial revolution or the Smart Factory, represents a new era of manufacturing characterized by advanced communication and connectivity, automation, and the integration of emerging technologies. This revolution leverages concepts such as machine-to-machine communication (M2M) and the Internet of Things (IoT) to enable seamless connectivity and data exchange between machines, systems, and humans. By harnessing the power of artificial intelligence, machine learning, robotics, and IoT, Industry 4.0 aims to create smart machines and systems that can autonomously analyze, diagnose, and optimize processes without human intervention. The goal is to enhance productivity, efficiency, and flexibility in manufacturing, leading to improved quality, reduced costs, and increased customization capabilities. Industry 4.0 builds upon the foundations of previous technological advancements while embracing new technologies to drive the next wave of industrial transformation. (Marr, 2018; Stearns, 2020; Zaleng, 2022)

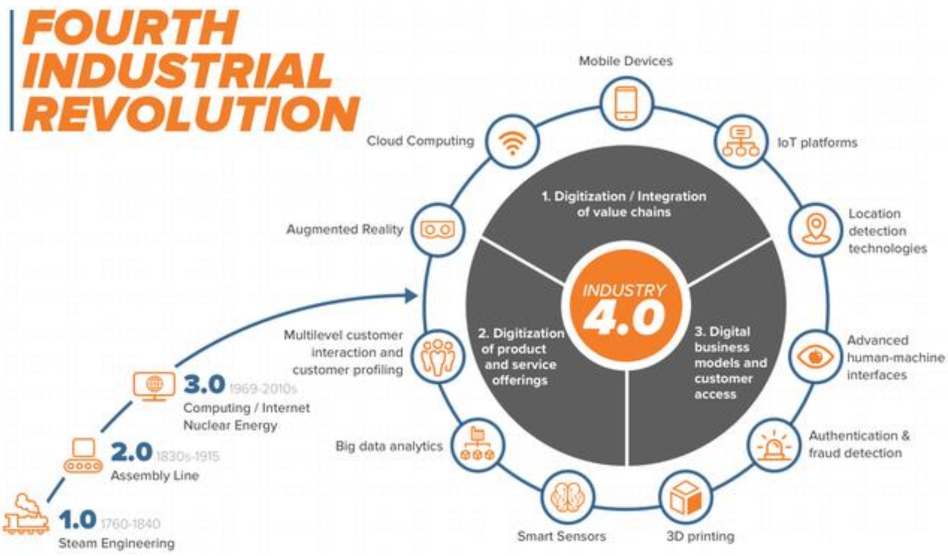

Figure 4. Segments of Industry 4.0 a reality. (ICT Works, 2019)

The 4th industrial revolution is driving a transformation in the oil and gas industry by enabling digitalization, automation, and the integration of emerging technologies. The supply chain cycle from extraction to final delivery as a product to consumers is in every step a continuous transformation, since operations are changing at every step in the supply chain. The reason is that companies involved in this cycle adopt new emerging technologies and digitize and simplify their processes.

The effectiveness of big data analytics, the industrial internet of things (IIoT), virtual reality, and artificial intelligence (AI) in the oil and gas industry relies on the integration of data with physical processes. Oil and gas companies' ability to successfully implement and sustain digitization initiatives will be crucial in reducing costs and maximizing production. This becomes especially important in an industry that is characterized by turbulence and volatility.

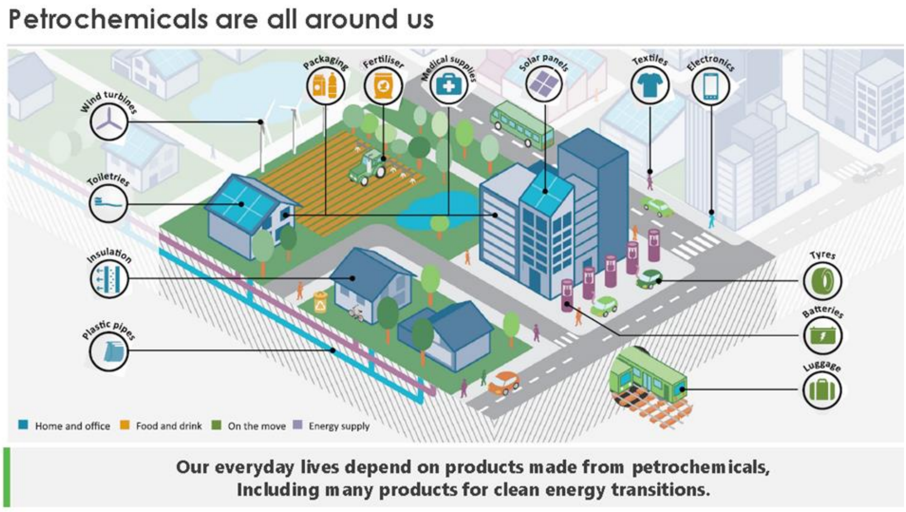

Figure 5. Petrochemicals are all around us. EU Refining Forum(International Energy Agency IEA, 2018)

The products of refining and other chemical processes serve as the foundation for oil and chemical companies seeking to achieve higher levels of operational excellence while increasing turnover and profitability. This is a major and critical competitive factor in the highly demanding environment of the oil and gas sector.

In the current dynamic work environment, the oil and gas industry is facing a range of challenges and opportunities driven by geopolitical factors, the discovery of new resources, global climate change, emerging energy sources, and advancing technologies. These developments are reshaping the market dynamics for petrochemical products and influencing consumer consumption patterns. As a result, the refining and oil and gas sectors are compelled to identify and adapt to new trends in order to remain competitive in a rapidly changing market. (International Energy Agency IEA, 2018)

In order to manage the new trends, the oil and gas industry has to strengthen the integration and adaptation of large-scale developments and use more profitable energy sources on the other hand, special attention and focus are given to the use of information technology adaptations that can provide amazing results within the refinery's operational capability and a modern, more efficient business execution model at the same time.(Speight, 2011) Furthermore, there is a focus on developing new technologies that aim to minimize the environmental impact of oil and gas operations and promote a more sustainable approach. These technologies are designed to create a greener footprint for the industry, aligning with the growing importance of environmental conservation and sustainability.

To address current challenges, the oil and gas industry should invest in new technologies like big data analytics, IoT systems, cloud computing, automation solutions, and artificial intelligence. These innovations provide competitive advantages and enable better management of industry operations. The adoption of IIoT, data analytics, big data, cloud computing, and other information technologies drives digital transformation in the oil and gas sector. The development of digital refineries, intelligent refineries, and smart refineries is crucial for improving operational excellence, production efficiency, and overall working framework. (Kunlun Digital Technology Co. Ltd., n.d.; Yuan et al., 2017)

Figure 6. Industrial Internet Platform AI enabled system for Oil and Gas Operations. (Kunlun Digital Technology Co. Ltd., n.d.) www.klszkj.com

The oil and gas industry can achieve optimization by adopting technologies like IIoT, big data, AI, and smart refineries. These technologies improve processes across the entire supply chain cycle, from exploration to sales. They enable planning, scheduling, and overall optimization, leading to cost reduction, enhanced reliability, safety, and more efficient operations. By leveraging these advancements, the industry gains real-time data monitoring, predictive maintenance, and informed decision-making capabilities, resulting in improved performance and competitiveness. Furthermore, smart refineries will achieve planning and scheduling optimization as well as overall optimization. (Douglas, 2003)

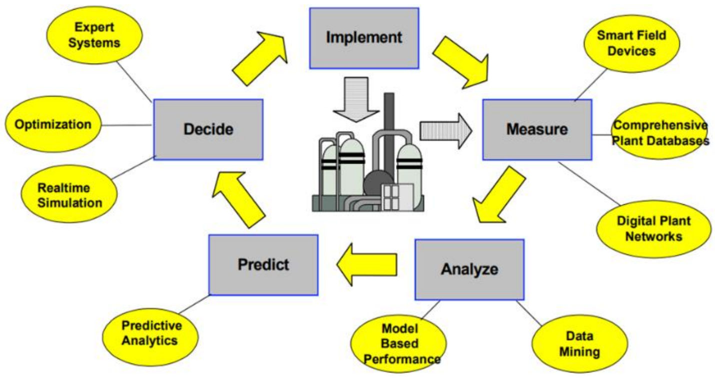

Figure 7. Enabling Technologies. (Douglas, 2003)

This will enable them to increase their competitive advantages, improve the flexibility and scalability of their operations, and move towards a more sustainable production system that is not only capable of meeting changing market demands but also responding to environmental pressures and demands.

Qing Wu and Dawei Zhang highlight that the primary objective of the digital refinery and intelligent refinery is to optimize the value generated throughout the industrial chain of refineries and other chemical industries. The digital refinery serves as the foundation, focusing on the digitalization of humans, equipment, and operations. This involves leveraging process automation and management information technology to enhance efficiency. By implementing a digital refinery, the operation of the facility becomes more transparent and visualized. This allows for better management and improves the efficiency of production and sales processes. The integration of digital technologies enables real-time monitoring, data analysis, and informed decision-making, leading to increased operational effectiveness and overall performance in the refinery and chemical industries..(Wu and Zhang, 2018)

Figure 8. Construction Plan of Smart Refinery. (Wu and Zhang, 2018)

Intelligent refinery as a follow-up to the smart refinery concept Extensive and deep knowledge enables greater optimization of processes and production, with the main focus being on effective operation. Intelligent refinery must prioritize model system adaptation, which includes, among other things, production system planning and scheduling optimization, operation optimization, an asset maintenance and equipment predictive analysis model, an inventory and logistics optimization model, and a sales and customer analysis model. The aforementioned key points play a crucial role in ensuring successful operations in the oil and gas industry today.

The key outcomes of implementing intelligent refinery technologies include achieving optimal control over production planning, scheduling, and operations. Additionally, the implementation enables effective lifecycle management and predictive maintenance practices. Another significant outcome is the optimization of energy consumption throughout the entire plant. Furthermore, integrated optimization of sales and logistics processes is facilitated, leading to improved efficiency. The primary objective is to establish smart refineries that can maximize the overall value of refinery enterprises. This involves the establishment of a smart supply chain, enabling clear and accurate coordination and optimization of each element within the entire industrial chain. From crude oil procurement to market sales, a smart supply chain enables effective management and maximization of the value chain. Ultimately, the focus is on achieving cost optimization in production and sales processes.(Wu and Zhang, 2018).

Buzzy terms and definitions of Digital transformation, Digital, Digitalization, Digitization

The terms "digital," "digitalization," and "digital transformation" are frequently used buzzwords that appear in media, company materials, and online articles. However, understanding their precise meanings can be challenging. We will try to solve this problem by giving a clear definition of each term and pointing out the most important differences between them.

Digital, digitalization, and digital transformation are interconnected concepts that revolve around the application of digital technology in various aspects of life.

Digitization, digitalization, and digital transformation describe the process of converting analog (non-digital) elements into a digital format. This involves transforming physical or analog data, such as text, images, or sound, into a digital representation that can be stored, processed, and transmitted electronically. It's important to note that digitization focuses on the conversion of data format without altering the underlying process significantly.

On the other hand, digitalization refers to the broader use and integration of digital technologies and tools in different domains, including business operations and interactions. It entails the adoption of digital solutions to enhance efficiency, improve decision-making, and generate new value. Digitalization goes beyond the conversion of analog data, emphasizing the utilization of digital technologies to transform existing processes, enhance customer experiences, and enable innovative business models.

Lastly, digital transformation encompasses organizational and cultural changes necessary to leverage digital technologies and drive fundamental shifts in business processes, strategies, and models. It involves reimagining and redefining operations, customer experiences, and value propositions through the integration of digital technologies. Digital transformation extends beyond the digitalization of specific functions, focusing on fostering a comprehensive digital mindset and capabilities throughout the organization to foster innovation, agility, and a competitive edge.

In summary, digitization refers to converting analog data into a digital format, digitalization involves utilizing digital technologies in various areas, and digital transformation entails strategically and comprehensively transforming business processes and models through the integration of digital technologies.

Digital

For the term "Digital" the following definitions can be applied:

Source	Definition
Cambridge Dictionary	*"Recording or storing information as a series of the numbers 1 and 0, to show that a signal is present or absent" example: digital data"* *"Using or relating to digital signals and computer technology" example: a digital recording* *"Showing information in the form of an electronic image" Example: a digital clock/display* *"Using a system that can be used by a computer and other electronic equipment, in which information is sent and received in electronic form as a series of the numbers 1 and 0" example : digital content/data/information* (Cambridge Dictionary, 2023)
Merriam Webster	*"Composed of data in the form of especially binary digits"* (Merriam Webster Dictionary, 2023)
Collins Dictionary	*"of, relating to, resembling, or possessing a digit or digits"* *"representing data as a series of numerical values"* *"designating or of data, images, sounds, etc. that are stored, transmitted, manipulated, or reproduced by a process using groups of electronic bits represented as 1 or 0"* *"A digital system is one that operates using ones and zeros rather than analog signals."* (Collins Dictionary, 2023)
Longman Dictionary	*"using a system in which information is recorded or sent out electronically in the form of numbers, usually ones and zeros"* (Longman Dictionary, 2023) *"digital electronic equipment receives sound and pictures from binary electrical signals (=signals using the numbers 0 and 1)"* (Longman Dictionary, 2023)
TechTarget	*"Digital describes electronic technology that generates, stores, and processes data in terms of two states: positive and non-positive. Positive is expressed or represented by the number 1 and non-positive by the number 0. Thus, data transmitted or stored with digital technology is expressed as a string of 0's and 1's. Each of these state digits is referred to as a bit (and a string of bits that a computer can address individually as a group is a byte)."* (TechTarget, 2023a)

Table 1. Definitions of term "Digital"

The term "digital" encompasses various meanings and interpretations. While many associate it with computers and data, it goes beyond that narrow definition. In its essence, "digital" refers to anything that can be represented by a series of binary states, such as true/false, on/off, or positive/negative. Digital technology is based on this fundamental concept of discrete and quantized information. It has revolutionized various fields and industries by enabling efficient storage, processing, and communication of data in a digital format.

Digitization

For the term “Digitization” the following definitions can be applied:

Gartner Glossary defines "digitization" as the process of converting analog information into digital form, without any substantial changes to the underlying process itself. (Gartner Glossary, 2023a) It involves the transformation of text, pictures, or sound into a format that can be processed by computers. Similarly, TechTarget defines "digitization" as the conversion of information into a digital format. (TechTarget, 2023b) These definitions highlight the core idea of converting analog data or information into a digital form that can be easily stored, manipulated, and transmitted using digital technologies.

Digitalization

According to the Gartner Glossary, "digitalization" refers to the utilization of digital technologies to transform a business model and create new opportunities for generating revenue and value. It involves the transition towards becoming a digital business. In a study conducted by J. Reis et al. in 2020, the term "digitalization" was explored, and various definitions from different scholars were compiled. These definitions aim to capture the essence of digitalization in the literature. (Reis et al., 2020)

Author	Definition
Maxwell and McCain	*"Digital technology takes information and breaks it down into its smallest components. By transforming an analogue signal into discrete pieces, digitalization makes it possible to manipulate information, text, graphics, software code, audio, and video in ways never before thought of, thus its informating, transforming capabilities"*
Hagberg et al.	*"Digitalization is one of the most significant on-going transformation of contemporary society and encompasses many elements of business and everyday life. Digitalization refers both to a transformation from "analogue" to "digital" (e.g. a shift from cash to electronic payments) and to the facilitation of new forms of value creation (e.g. Accessibility, availability, and transparency)"*
Clerck	*"Digitalization is defined as the use of digital technologies and of data in order to create revenue, improve business, replace/transform business processes and create an environment for digital business, whereby digital information is at the core"*
Lenka et al.	*"The industrial management literature defines the digitalization as the phenomenon of intelligent connected machines that information and digital technologies power"*
Machekhina	*"Digitalization means transformation of all information types (text, sound, visuals, video and other data from various sources) into the digital language"*
Parviainen et al.	*"The action or process of digitizing; the conversion of analogue data (esp. in later use images, video, and text) into digital form"*
Thorseng and Griot	*"The transformation of existing socio-technical structures that were previously mediated by non-digital artefacts or relationships into ones that are mediated by digitized artefacts and relationships with newly embedded digital capabilities"*
Valenduc and Vendramin	*"The term "digitalization" is not the irruption of a new revolution, but the pervasive synergy of digital innovations in the whole economy and society"*
Crittenden et al.	*"Digitalization creates new forms of interaction between companies and customers through channels"*

Table 2 Digitalization Definitions. (Reis et al., 2020)

From the above-mentioned definitions, it is understandable that the term "digitalization" has perhaps the greatest gravity. I believe that this is the starting point from which we can wonder if our enterprise is in the right phase to move forward. So, it is very crucial to understand and comprehend the terms and their meanings fully and in depth.

Undoubtedly, our society is progressing towards a more digitalized state, where digital solutions play a central role in transforming daily interactions among individuals, businesses, government services, and overall operational practices. A more precise understanding of "digitalization" entails the adoption and application of digital technology and digitized data as valuable assets. Its purpose is to generate added value and revenue, enhance business operations, and foster improved relationships with stakeholders, such as customers. Moreover, digitalization aims to cultivate a digital culture where digital information serves as the foundation and core element within the organization. This definition draws a clear distinction between digitalization and digitization, where digitalization involves utilizing digitized data with digital tools to create value, improve business and customer relationships, and establish a digital-oriented organizational culture.

Digital Transformation,

Digital transformation is not something you can purchase as a solution, a product, or a service. It is understandable that digital transformation affects the information technology infrastructure of the company.

According to the Gartner Glossary[1], the term "digital transformation" encompasses a wide range of initiatives and can have different meanings depending on the context. It can refer to various activities, from IT modernization efforts like adopting cloud computing, to optimizing existing digital processes, to developing new digital business models. (Gartner Glossary, 2023b)

[1] https://www.gartner.com/en/information-technology/glossary/digital-transformation

Different organizations and sources may provide slightly different definitions of "digital transformation" based on their specific perspectives and areas of focus. Citrix defines digital transformation as the strategic adoption of digital technologies to improve processes, productivity, customer and employee experiences, risk management, and cost control. According to Citrix[2], digital transformation encompasses a wide range of tools, solutions, and processes, and an effective strategy should be tailored to each organization's unique needs. (Citrix, 2023)

On the other hand, I-SCOOP[3], an organization focused on digital business and transformation, defines digital transformation as a broader concept involving cultural, organizational, and operational changes across an organization, industry, or ecosystem. Their definition emphasizes the integration of digital technologies, processes, and competencies at all levels and functions in a staged and strategic manner. (I-SCOOP, 2023)

These definitions highlight different aspects of digital transformation, but both emphasize the need for organizations to leverage digital technologies and adapt their operations to achieve desired outcomes. The specific interpretation and approach to digital transformation may vary depending on the organization's goals, industry, and context. The adoption of new technology and the need for organizational changes are crucial aspects of digitalization and digital transformation. The process goes beyond the mere implementation of technology and involves reshaping business processes, culture, and operations to leverage the full potential of digital tools and technologies. (Boyer, 2018)

Digital transformation is a comprehensive and holistic journey that requires a strategic approach and involvement from top management. It entails aligning the organization's strategy and goals with digital initiatives, redefining processes to optimize efficiency and effectiveness, and fostering a culture of innovation and adaptability. By embracing digital transformation, organizations aim to create added value, enhance customer experiences, and drive growth and competitiveness in the digital age. It encompasses all aspects of the organization and requires a systematic and integrated approach to

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[2] https://www.citrix.com/glossary/what-is-digital-transformation.html

[3] https://www.i-scoop.eu/digital-transformation/

achieve a fully digital working environment. While definitions may vary, the core concept remains consistent: digital transformation is a multidimensional process that involves technology, organizational change, and the integration of digital practices across the entire organization. (Arild Haraldsen, 2018)

Digitalization and digital transformation are two distinct but interconnected processes. Digitalization refers to the process of utilizing digitized data, typically in the form of digital files or information, and employing digital tools and technologies to work with and manage that data effectively. It involves the conversion of analog or physical assets into digital formats, enabling easier storage, retrieval, and manipulation of information.

On the other hand, digital transformation goes beyond the use of digital tools and focuses on utilizing digital technology to fundamentally change and improve business processes, strategies, and customer experiences. It encompasses the adoption of digital technologies to optimize operations, enhance efficiency, foster innovation, and drive growth within an organization.

In summary, digitalization is about leveraging digitized data and digital tools, while digital transformation involves a broader organizational shift towards utilizing digital technology to revolutionize and improve various aspects of the business. Summarizing the above-mentioned terms and definitions, the road map for digital transformation begins with:

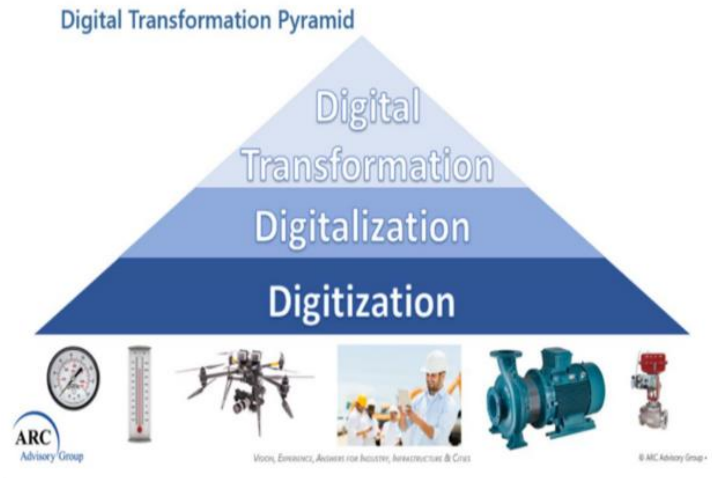

Figure 9. Digital Transformation Pyramid. ARC Advisory Group (Sen Gupta, 2020)

Digitization is the initial step of converting physical objects or analog information into a digital format. It serves as the starting point for organizations to embark on a digital transformation journey, paving the way for a fully digital work environment. By digitizing resources, businesses can enhance accessibility, searchability, and shareability of information, facilitating more efficient and streamlined operations. (Sen Gupta, 2020) as it lays the foundation for an organization to move towards a fully digital working environment.

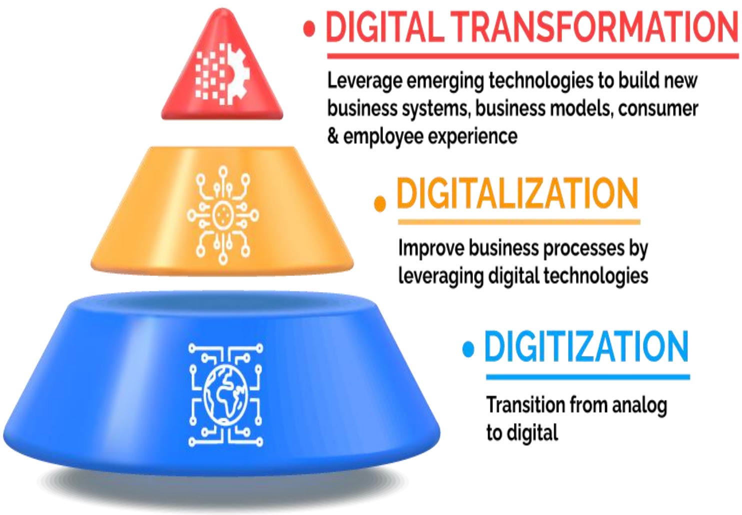

Figure 10. Digital Transformation Pyramid. (Quixy, 2023)

Digitization is a vital first step in digital transformation, bridging the physical and digital worlds. It involves converting analog information into digital formats, enabling efficient data storage, analysis, and automation. Digitization sets the foundation for leveraging advanced technologies and driving operational efficiencies.

By digitizing physical assets and processes, organizations can harness the power of technology to create cost savings, improve efficiency, and achieve improved customer satisfaction (Brusati, 2023; Quixy, 2023; Sen Gupta, 2020)

"Digitalization" means making processes possible or making them better by using and taking advantage of digital technologies and the digitized data collected from processes and interactions. Digitalization is the subsequent step after digitization. While digitization focuses on converting analog information into digital formats, digitalization involves leveraging digital technologies to enhance processes and operations.

Digitalization enables greater automation, control, and efficiency in various industrial processes. etc.(Brusati, 2023; Quixy, 2023; Sen Gupta, 2020)

It is obvious that we have improved productivity efficiency and, as a result, reduced costs in this step, but the fundamental point that must be made clear is that, while digitalization improves and updates an existing process or processes, it does not change them because it only changed the enabler, from human-driven to software-driven.

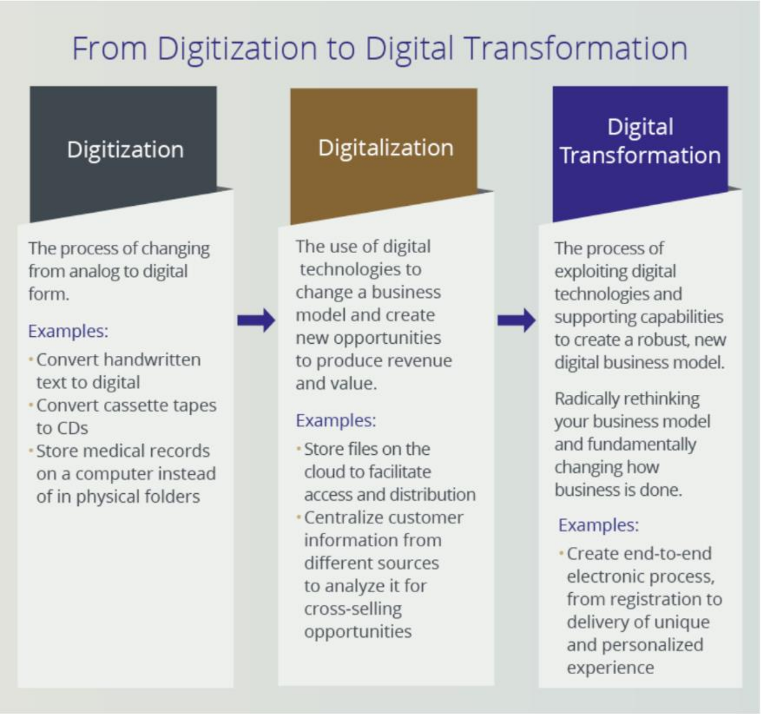

Figure 11. From Digital Transformation path. (Brusati, 2023)

The final step Digital Transformation. A transformation enabled by digitalization. At the heart of digital transformation is the change in business processes that digital technologies make possible or force. To get from a low-level digital working environment to a fully digitalized one.(Brusati, 2023; Quixy, 2023; Sen Gupta, 2020)

Figure 12 From Digitization to Digital Transformation. (Next Service, 2020)

For example, physical process control could shift from being human-controlled to being monitored and controlled remotely via intelligent devices, with the human factor acting only as a supervisor.

Digital transformation has a significant impact on the roles and responsibilities of employees within organizations. As businesses embrace digital technologies, it becomes essential to assess how these technologies will reshape job functions and require new skills and competencies. To navigate the impact of digital transformation on employees, businesses should prioritize employee training and upskilling programs to ensure their workforce remains relevant and adaptable in the digital era. Additionally, fostering a culture of continuous learning, innovation, and collaboration can help employees embrace digital technologies and contribute to the organization's overall digital transformation journey.

Digital Transformation in Oil and Gas Industry

The rapid advancement of information technologies, especially the emergence of new generation technologies like cloud computing, big data analytics, and artificial intelligence (AI), has accelerated the process of digitalization. The convergence of the physical and virtual realms has played a vital role in driving digitalization as a transformative force in various industries, fostering innovation and driving efficiency. According to Qi et al. (2021), digitalization progresses through four distinct phases: digital enablement, digitalization assistance, digital control and linkage, and cyber-physical integration. These phases represent the stages of development in digitalization, depicting the increasing integration of digital technologies and their impact on industries. (Qi et al., 2021)

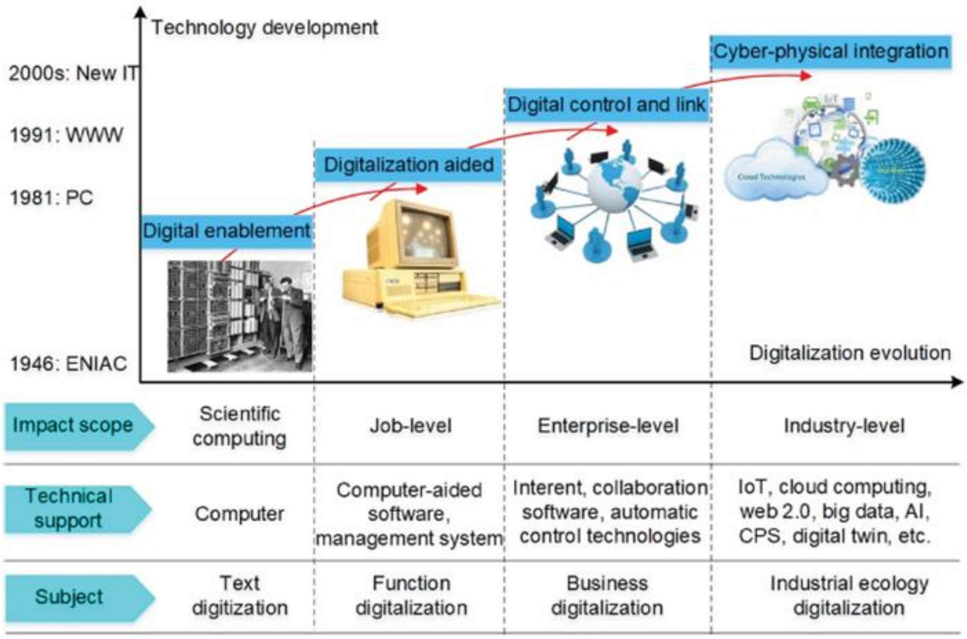

Figure 13. Evolvement of digitalization paradigm. (Qi et al., 2021)

Indeed, digital transformation plays a crucial role in the chemical industry, enabling leading corporations to optimize asset utilization and enhance manufacturing efficiency. By adopting digital technologies and leveraging data analytics, chemical companies can achieve higher levels of automation, process optimization, and integration across multiple plant sites and value chains. This allows for improved operational visibility, streamlined workflows, reduced downtime, and enhanced overall productivity. The digital transformation of the chemical industry paves the way for smarter and more sustainable operations, enabling companies to stay competitive in a rapidly evolving market. Several leading petrochemical companies are adopting and utilizing digital transformation as one of their fundamental innovations to maximize asset utilization through increased production efficiency, and integrated value chains. (Lu et al., 2019)

A basic or vital concern or a key challenge for petrochemical companies is how to accelerate the value of the enterprise by identifying and implementing methods to convert operations quicker than the competitors.

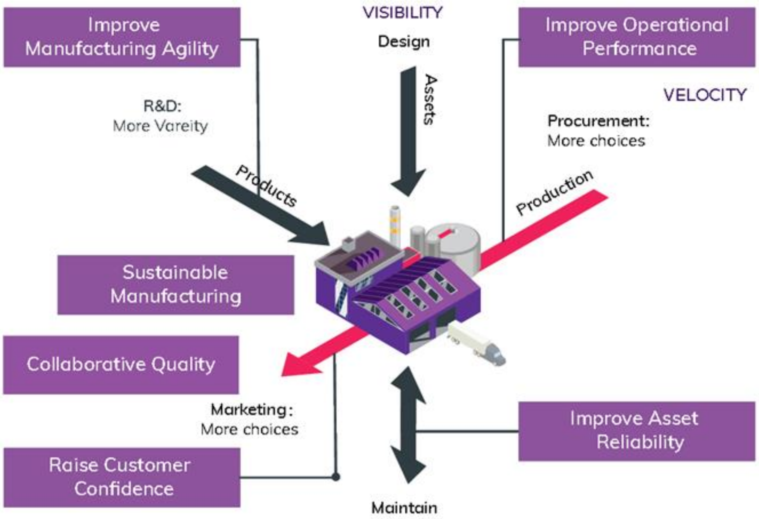

Figure 14. Value drivers for digital acceleration. (AVEVA Group, 2019)

In the Petrochemical industry, there are numerous important value drivers for advancing digital transformation. Leading petrochemical companies are implementing digital transformation at faster rates than their competitors, disrupting their market portfolio shares as a result. According to AVEVA divides the petrochemical plants into two lifecycles.

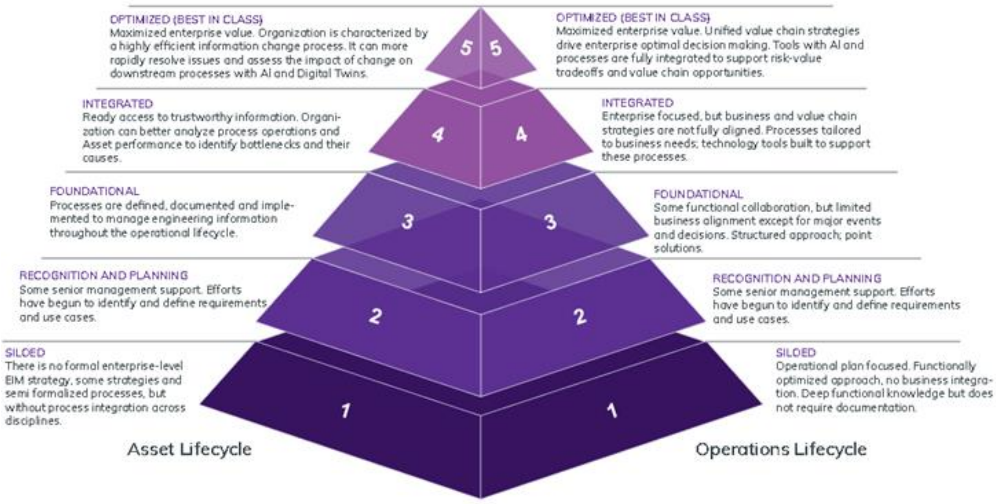

Figure 15. Asset - Operation Lifecycle. (AVEVA Group, 2019)

- the Asset Lifecycle which contains the plant and process design stage, the procurement stage, the construction stage, the maintenance stage, and any future revamps and updates stage.

- the Operations Lifecycle which contains the monitoring and controlling phase, the planning and scheduling phase, and any other various approaches to production optimization.

Obviously, the advantages in all stages and phases are visible in the Asset and Operation Lifecycle. By leveraging advanced technologies and real-time data analysis, businesses can achieve enhanced productivity and efficiency in evaluating the collected data and information. This enables better decision-making, predictive maintenance, optimized asset performance, improved operational visibility, and overall cost reduction. The integration of digital solutions across the lifecycle brings about significant improvements in asset management, operations, and maintenance practices.

Digital Maturity Model

For the adaption of the digital transformation actions, there is the need to measure and establish the basis meaning the digital maturity of the company. To do that a framework or a toolset is used known as the digital maturity model.

Maturity models aim to guide and help the enterprises to evaluate and assess their current status and level of competence in every and each functional, and organizational area. By measuring its level of maturity an organization is able to undertake and build the type of functions that need to change in order to drive to an increased level of maturity.

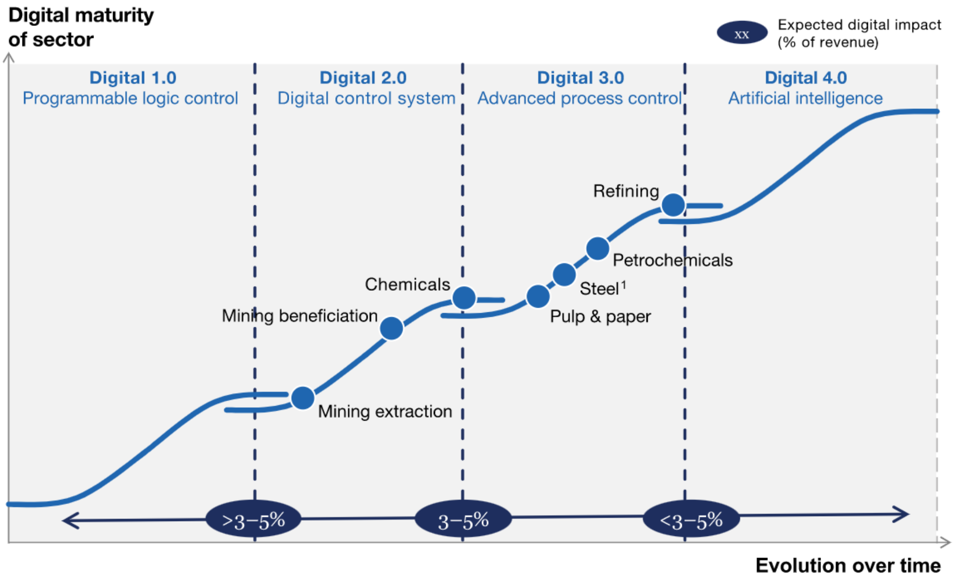

Figure 16. Digital Maturity Level per Industry sectors. (Noterdaeme et al., 2018)

As per Noterdaeme et al., according to the above figure we have the following conclusions.

Digital 1.0 At this level all the companies move forward to the next level since programmable logic control are serve only basic functions of automation.(Noterdaeme et al., 2018)

Digital 2.0 represents a typical level of digitization where businesses have implemented automated processes operated by distributed control system (DCS) technologies. Additionally, enterprise resource planning (ERP) systems are utilized to manage operations. This level of digital transformation enables improved control and coordination of processes, enhanced operational efficiency, and better integration of various business functions. (Noterdaeme et al., 2018)

Digital 3.0 represents an advanced stage of digitization where businesses utilize sophisticated automation and control technologies, such as multipurpose robots, advanced process control systems, and real-time optimizers. It involves the integration of artificial intelligence (AI) and machine learning (ML) into business processes, enabling enhanced automation, optimization, and real-time data analysis for informed decision-making. A robust data infrastructure facilitates asset optimization and value realization, while manufacturing execution systems (MES) and data analytics drive real-time monitoring and decision-making on the shop floor, leading to improved efficiency, product quality, and competitiveness in the industry. (Noterdaeme et al., 2018)

Digital 4.0. Represent a future stage of digital maturity but not far away. At this point, businesses are utilizing artificial intelligence, process control, and even machine learning to maximize asset value and improve asset performance.(Noterdaeme et al., 2018)

All industrial sites should have real-time information flowing automatically, allowing for centralized data-driven decision-making. This approach can lead to increased efficiency, reduced downtime, and cost savings. Additionally, predictive maintenance can be implemented to prevent equipment failures and optimize maintenance schedules.(Noterdaeme et al., 2018)

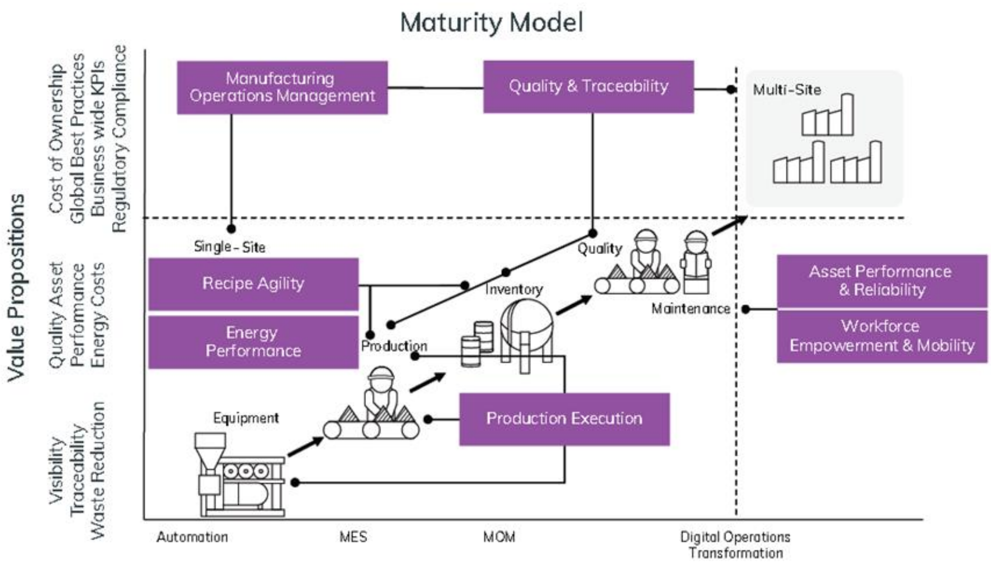

Figure 17. Digital Maturity Model for Petrochemical Companies. : (AVEVA Group, 2019)

Digital transformation enables automation of management tasks and seamless information flow. It includes automated data collection, efficient data management, real-time information sharing, process automation, analytics for insights, flexible software solutions, enhanced accessibility, integration of systems, and continuous improvement. These advancements streamline operations, improve decision-making, and boost overall business performance. The digital Maturity model is the framework that acts as a basis in order to evaluate and determining policy and classifying the areas of interest where further actions for improvements is necessary. It is a roadmap of guidance for the implementation of the digital transformation a valuable tool for guiding a company's journey towards becoming a digitally mature organization. It serves as a strategic plan, outlining the steps, actions, and milestones required to achieve successful digital transformation. Obviously, the digital maturity models in each type of industry can be different with more or fewer levels and the same is valid also for the companies in the same area.(AVEVA Group, 2019)

CHAPTER 3

ISA 95 Enterprise-Control System Integration Suite of Standards

The International Society of Automation (ISA, 2022) is a non-profit organization founded in the United States. The professional association mentioned is dedicated to serving engineers, technicians, and management professionals involved in the field of industrial automation.

The International Society of Automation made and presented the standard ANSI/ISA 95.00.0X series, which is called *"Enterprise Control System Integration."* The most important problem to solve was how to standardize all integration practices and methods between of the two levels, the enterprise level and the control level in order to develop or to make a model of the business that includes all of its business functions, manufacturing functions, control functions, and information functions for data exchange.(Gifford and Daff, 2017)

To make sure everyone knows the terms used to talk about the business and all of its functions (business processes, manufacturing control, data exchange), the ISA created a series of standardized terms and concepts that can be used by everyone.(Monchinski, 2020)

In the 1990s, a detailed study was conducted with the goal of developing a common landscape and set of rules for all parties involved. Extensive research and study were done on all of the existing good practices and standards. All of the existing models for integrating the two levels (enterprise and control) did not have enough depth or detail and were not up-to-date in order to reach the main goal, structure, and did not provide enough "common ground" for everyone.(Jimenez, 2021)

The Purdue Reference Model for Computer Integrated Manufacturing (CIM) with a hierarchical structure was used as a basis and then added to. The Purdue Reference Model (Theodore J. Williams, Purdue University, 1990) (Wikipedia, 2023) for Computer Integrated Manufacturing (CIM) was a revolutionary model that took a holistic approach to solve the challenges associated with integrating enterprise and control level systems.

So, the main goal was not only to solve the problems that came up as automated interfaces between enterprise level and control system level evolved but also to cut costs and make sure that everyone used the same terms, had the same requirements, and had the same specifications. It can be used in all industries sectors and applicable for all kinds of processes such as continuous processes, batch processes, repetitive processes, and discrete processes.(Monchinski, 2020)

The Enterprise Control System Integration standards series is made up of the following parts, each with a publication date: We will try to define and explain the main goal and importance of each part of the ISA-95 standard series, focusing mostly on the most important sections.

In following table present the parts of the standard ANSI/ISA-95.00.XX series that were adopted from the ISA site (name and date of issue).(ISA, 2022)

ISA Code	Title	Issue Date
ANSI/ISA-95.00.01 (IEC 62264-1 Mod)	*Enterprise-Control System Integration. Part 1: Models and Terminology*	*2010*
ANSI/ISA-95.00.02	*Enterprise-Control System Integration. Part 2: Objects and Attributes for Enterprise-Control System Integration*	*2018*
ANSI/ISA-95.00.03	*Enterprise-Control System Integration. Part 3: Activity Models of Manufacturing Operations Management*	*2013*
ANSI/ISA-95.00.04	*Enterprise-Control System Integration. Part 4: Objects and Attributes for Manufacturing Operations Management Integration*	*2018*
ANSI/ISA-95.00.05	*Enterprise-Control System Integration. Part 5: Business-to-Manufacturing Transactions*	*2018*
ANSI/ISA-95.00.06	*Enterprise-Control System Integration. Part 6: Messaging Service Model*	*2014*
ANSI/ISA-95.00.07	*Enterprise-Control System Integration. Part 7: Alias Service Model*	*2017*
ANSI/ISA-95.00.08	*Enterprise-Control System Integration. Part 8: Information Exchange Profiles*	*2020*

Table 3 Standard ANSI / ISA 95.00.0x series. (ISA, 2022)

Standard ANSI/ISA-95.00.01, Part 1 "Models and Terminology," has the objective of establishing standardized definitions for fundamental terms. This includes defining the interface content that facilitates the interaction between enterprise operations, functions, or activities and manufacturing control operations, functions, or activities. These interfaces primarily pertain to the connections between Levels 3 and 4 within hierarchical models.(ANSI/ISA-95.00.01, 2010)

The main goal is to make interface terminology more uniform and consistent, to reach a high level of common language, and to reduce the risks, costs, and other possible mistakes that come with putting these interfaces in place.

The ANSI/ISA-95.00.01 standard, emphasizes the importance of achieving high levels of adaptability and integration between enterprise systems and control systems. It provides a comprehensive description of hierarchy models for activities involved in manufacturing control enterprises, as well as operations at the business logistics level. Additionally, it includes an equipment hierarchy model for manufacturing control equipment. The hierarchy structure and data flow models outlined in the standard cover a wide range of functions within a manufacturing business framework. However, not all of these functions are required for manufacturing control and systems. According to the standard, certain criteria are used to describe and determine the information flows and functions to be employed. (ANSI/ISA-95.00.01, 2010)

The ANSI/ISA-95.00.01 standard considers several criteria for describing and determining the information flows and functions to be utilized. These criteria include:

- Criticality of the function to maintain a high level of regulatory compliance: This criterion ensures that functions adhere to safety standards, environmental regulations, and conformity with good manufacturing practices.(ANSI/ISA-95.00.01, 2010)

- Criticality of the function to maintain plant reliability: Functions that are crucial for ensuring the reliability and continuous operation of the plant are given priority. (ANSI/ISA-95.00.01, 2010)

- Impact of the function on the life cycle of the facility: Functions are evaluated based on their impact during different phases of the facility's life cycle, including operation, design, construction, and disposal phases.(ANSI/ISA-95.00.01, 2010)

- Essential information required by operators for effective facility operation: Functions that provide necessary information to operators for smooth and efficient facility operation are prioritized.(ANSI/ISA-95.00.01, 2010)

These criteria help in defining the importance and relevance of functions within the manufacturing control framework outlined by the standard.

Based on the criteria mentioned earlier, the boundary between the enterprise control system and non-control functions can be identified by the information flow path between functions that are categorized as part of the control domain and those that are not. In the accompanying figure, the boundaries between control and non-control functions are illustrated using a data flow model. The information path clearly delineates the extent of the enterprise control system by connecting functions marked as within the control domain and distinguishing them from functions outside of this domain. By visually representing the boundaries, the figure provides a clear understanding of the information flow and the separation between control and non-control functions within the enterprise control system.(ANSI/ISA-95.00.01, 2010)

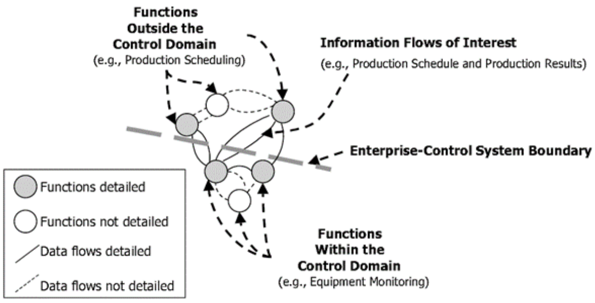

Figure 17. Enterprise control system interface. (ANSI/ISA-95.00.01, 2010)

In ANSI/ISA-95.00.02 Part 2, the focus is on explaining the theoretical interface content exchanged between manufacturing control functions and other enterprise functions. Specifically, it addresses the interface between Level 3 (manufacturing systems) and Level 4 (business systems) in the hierarchical model, as defined in Part 1. The primary objective is to minimize risks, costs, and errors associated with implementing integration. The main purpose of Part 2 is to define the object models and attributes of the information exchanged, as outlined in Part 1. Detailed instructions are provided in this section to guide the implementation of the integration described in Part 1. By following these instructions, organizations can effectively establish and manage the exchange of data between manufacturing control functions and other enterprise functions, thereby optimizing the integration process. (ANSI/ISA-95.00.02, 2018)

ANSI/ISA-95.00.03 Part 3 of the standard defines the activity models of manufacturing operations management, enabling enterprise systems to effectively handle and control system integration. These activities align with the object model definitions provided in Parts 2 and 4. They specifically pertain to the interactions between level 4 functions, such as business planning and logistics, and level 2 functions, such as process control, as outlined in ANSI/ISA-95.00.01-2010 (IEC 62264-1 Mod) Part 1. The scope of ANSI/ISA-95.00.03 Part 3 is focused on presenting a model of manufacturing operations management activities within the context of level 3 functions. It also includes a list of data that is shared between level 3 activities. Additionally, this part of the ISA-95 standard describes the attributes associated with manufacturing operations management activities and elucidates the roles these activities play within a business process model. (ANSI/ISA-95.00.03, 2013)

In ANSI/ISA-95.00.04 Part 4 of the standard, the focus is on the object models and attributes that are involved in the exchange of data between manufacturing operations management activities described in Part 3. These models and terms presented in both Part 3 and Part 4 serve as "best practices" for integrating manufacturing operations management systems throughout their entire life cycle. By following these models and terms, organizations can enhance the ability of manufacturing operations management systems to work together more effectively. Understanding the roles, attributes, and terms associated with these systems allows companies to identify opportunities for improvement and create more efficient systems. Ultimately, this understanding leads to more effective integration of different systems within the manufacturing operations management ecosystem and allows businesses to achieve better operational performance. (ANSI/ISA-95.00.04, 2018)

In ANSI/ISA-95.00.05 Part 5 of the standard, the focus is on explaining transactions in terms of information data exchanges between applications that are associated with business and manufacturing activities at Levels 3 and 4. The objective of these data exchanges is to facilitate the collection, retrieval, sending, and storage of information, ultimately aiding in the integration of enterprise-control systems. By understanding the roles, attributes, and terms associated with manufacturing operations management systems, companies can establish seamless data exchanges between their applications. This enables efficient integration of the enterprise control system, allowing for improved coordination and synchronization of activities across different levels and functions of the organization. The goal is to streamline information flow and enhance the effectiveness of enterprise-control system integration. (ANSI/ISA-95.00.05, 2018).

In ANSI/ISA-95.00.06 Part 6 of the standard, the focus is on establishing a standard interface for information exchange between systems. This part specifically addresses the model of messaging services used for information data interactions across Levels 3 and 4, as well as within Level 3 itself, for applications used between them to perform business and manufacturing activities.

The purpose of Part 6 is to define a standardized approach for exchanging messages and information between different systems involved in enterprise-control system integration. This ensures that the communication between systems is consistent, reliable, and efficient, facilitating seamless information flow and coordination of activities.

By adopting the messaging services model described in Part 6, organizations can establish a common framework for data exchange, enabling interoperability and smooth integration between various applications and systems at different levels of the organization. This promotes effective collaboration and synchronization of business and manufacturing activities, ultimately contributing to improved operational efficiency and performance.(ANSI/ISA-95.00.06, 2014)

In ANSI/ISA-95.00.07 Part 7 of the standard, the focus is on how applications within the manufacturing operations domain and applications in other domains exchange independent services and messages. Specifically, this part addresses the association and mapping of aliases, as well as the context that accompanies them.

By defining the rules and mechanisms for alias association and mapping, ANSI/ISA-95.00.07 Part 7 facilitates the integration of applications from various domains, allowing them to exchange information, services, and messages effectively. This helps establish a common understanding and context among different systems, enhancing collaboration and data interoperability.Ultimately, the guidelines and specifications presented in Part 7 enable organizations to achieve better integration between applications in the manufacturing operations domain and applications in other domains, leading to improved communication, coordination, and overall system performance. (ANSI/ISA-95.00.7, 2017)

In ANSI/ISA-95.00.08 Part 8 of the standard, a method is specified to define information data exchange profiles for specific groups of implementations of ISA-95 models. These information data exchange profiles serve as a means to describe the object models that are shared on interfaces between Level 4 and Level 3 (horizontal integration) or between Level 3 activities (vertical integration).The primary purpose of Part 8 is to facilitate interoperability between systems from different manufacturers by providing a standardized approach to defining information data exchange profiles. These profiles enable systems to communicate effectively and exchange data using a common language. By following the guidelines and specifications outlined in Part 8, organizations can ensure that their systems adhere to a consistent framework for exchanging information. This promotes seamless integration and communication between systems, regardless of the specific implementations or manufacturers involved. Ultimately, ANSI/ISA-95.00.08 Part 8 plays a crucial role in enabling interoperability and system-to-system communication by providing a standardized method for defining information data exchange profiles. This allows for efficient integration of systems from different manufacturers and fosters the development of a common language for effective data exchange. (ANS/ISA -95.00.08, 2020)

Manufacturing Operations Management.

Manufacturing operations management (MOM) encompasses activities that involve physical equipment (machines), human effort (work hours), and information systems (software). It involves organizing and managing the workforce, equipment, materials, and energy in converting raw materials or parts into finished products. MOM aims to optimize productivity, minimize costs, ensure quality control, and streamline processes for operational excellence. (ANSI/ISA-95.00.03, 2013)

Information systems play a crucial role in manufacturing operations management (MOM) by handling and managing information related to various resources such as labor, materials, and equipment. These systems provide real-time and historical data on resource status, including schedules, capabilities, usage, and historical records. By integrating these activities into a set of procedures, MOM aims to optimize overall performance and efficiency in manufacturing operations. This includes activities such as forecasting, maintenance, scheduling, and resource allocation to ensure optimal productivity and operational excellence. (ANSI/ISA-95.00.03, 2013)

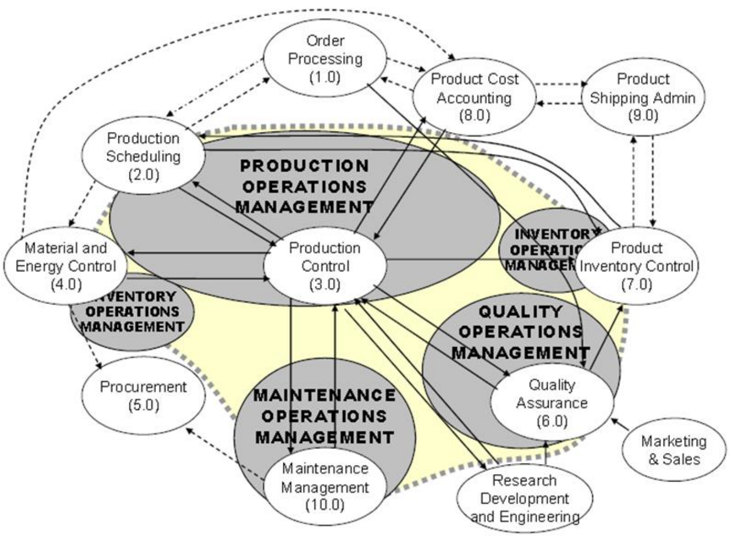

Figure 18. Manufacturing operations management model. (ANSI/ISA-95.00.03-2005).

The figure provided illustrates a model of activities in Manufacturing Operations Management (MOM). The heavy dotted line represents the interface between levels 3 and 4, where these activities intersect. The shaded areas represent the four parts of MOM, along with their corresponding activities:

Management of Production Operations:

- Production Scheduling (Level 3): Activities related to creating production schedules, including determining the sequence and timing of production tasks.

- Production Control (Level 3): Activities involved in monitoring and controlling production processes, ensuring they align with the defined schedules and targets.

Maintenance Operations Management:

- Maintenance Management (Level 3): Activities focused on managing and coordinating maintenance tasks, including preventive and corrective maintenance activities.

Quality Operations Management:

- Quality Assurance (Level 3): Activities aimed at ensuring product quality and compliance with quality standards through inspections, testing, and quality control measures.

Inventory Operations Management:

- Product Inventory Control (Level 3): Activities related to managing and controlling product inventory, including tracking stock levels, replenishment, and inventory optimization.

- Material and Energy Control (Level 3): Activities involved in managing and optimizing the use of materials and energy resources within the manufacturing operations.

These parts and activities within MOM are essential for effective production management, maintenance, quality control, and inventory control in manufacturing facilities.

Functional hierarchy Model

The functional hierarchy model consists of multiple levels that represent different aspects of the manufacturing process. At the top level, there is business planning and logistics, which focuses on overall planning and coordination. The next level is manufacturing operations and control, which deals with the actual execution of production tasks. This level can further be divided into batch, continuous, or discrete control depending on the production strategy.

At levels 2, 1, and 0, specific functions related to cell or line supervision, operations, and process control are defined. These functions may vary based on the production strategy employed by the organization.

Level 3, Manufacturing Operation Management (MOM), is responsible for the effective functioning of the Manufacturing Execution System (MES). This includes activities such as operations control, reporting, material storage and handling, and data management. Data collected and evaluated at this level encompasses inventory, production, quality, energy consumption, raw materials, spare parts, and other relevant information, which can be used to improve the production process.

Level 4, known as Business Planning and Logistics, encompasses activities such as creating a basic production schedule, managing raw material and spare parts usage, monitoring availability and delivery, and handling shipping logistics. It also involves gathering and maintaining equipment use and history data for planning preventive and predictive maintenance. The production schedule can be modified based on the input and needs from other levels.

The functional hierarchy model provides a framework for organizing the different components of a system based on their functionality and time requirements. It focuses on the interface between levels 4 and 3, where decisions are made and coordination takes place. Levels 0, 1, and 2, often referred to as the shop floor, represent the actual production processes, handling activities, sensors measurements and gathering information and data are in this level. These levels are specific to the type of control and operation, such as batch, continuous, or discrete. Level 3 is responsible for coordinating the activities across different levels. It involves analytical functions like forecasting, scheduling, and process management, ensuring efficient coordination and optimization of the production processes.

The functional hierarchy model described in the standard outlines the specific functions performed at each level within a defined time frame. Here is a summary of each level and its corresponding activities:

Level 0: Physical Production Processes.

Activities: Actual execution of the physical production processes, which can be continuous, batch, or discrete.

Level 1: Sensing and Manipulating Production Processes

Activities: Monitoring and collecting data from the physical production processes, including sensing and measurement.

Level 2: Control of Production Processes

Activities: Monitoring, supervising, and controlling the physical production processes using technologies such as PLC, DCS, or SCADA systems. The tasks at this level revolve around monitoring, supervising, and controlling the physical processes. It may involve the use of programmable logic controllers (PLC), distributed control systems (DCS), or supervisory control and data acquisition (SCADA) systems.

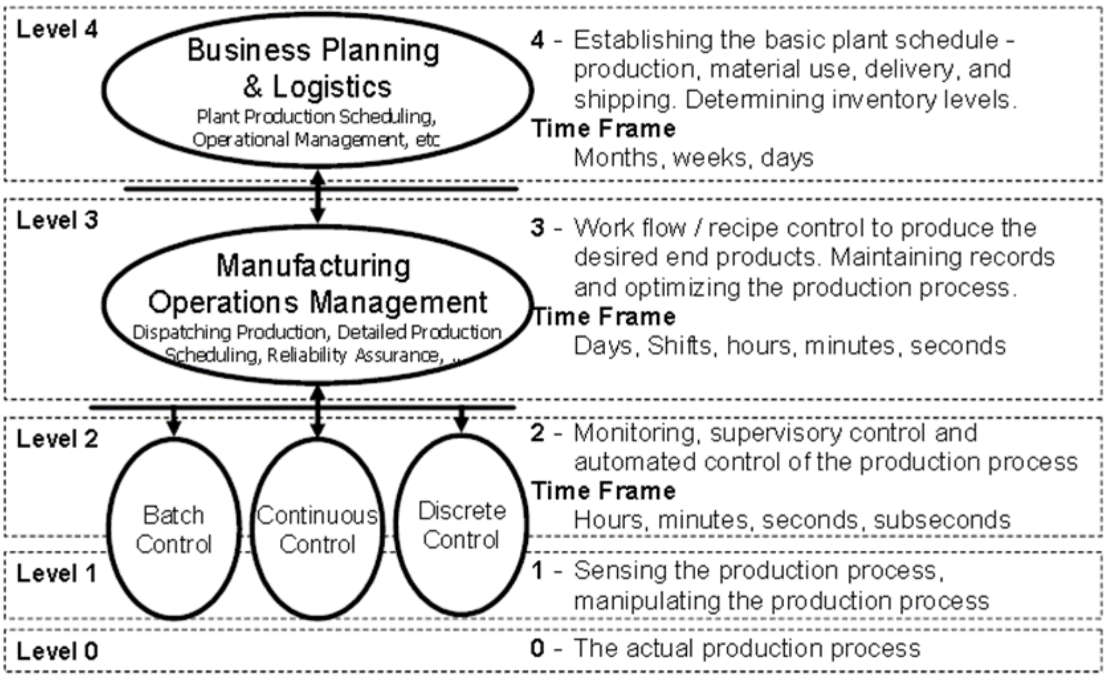

Figure 19 Multi-Level functional hierarchy of activities. (ANSI/ISA-95.00.03-2005).

Level 3: Workflow Management and Coordination

Activities: Managing the workflow to deliver the desired final products, including tasks such as process coordination, optimization, and data storage (history logs and other data). This level encompasses the activities of workflow management aimed at delivering the desired final products. It includes tasks such as data storage (history logs and other data), process coordination, and optimization.

Level 4: Business Management and Planning

Activities: Business-related activities for managing the manufacturing facility, including plant scheduling, inventory management, material usage and delivery, and ensuring compliance with business objectives. This level encompasses the business-related activities necessary for managing a manufacturing facility. It involves activities such as plant scheduling (including material use, delivery, and shipping), inventory management, and ensuring timely delivery of materials for production.

The information and data flow shared at Level 3 are vital for the activities and tasks performed at Level 4. It enables effective coordination and optimization of manufacturing operations, ensuring that business requirements are met efficiently.

The flow of information and data between these levels is crucial for effective manufacturing operations management, enabling coordination, optimization, and decision-making to achieve production goals efficiently.

The criteria and conditions for defining activities below level 4 are that the activity must be directly related to the manufacturing operation, including information and data about personnel, equipment, and materials. The criteria and conditions for defining activities below level 4 in the functional hierarchy model are as follows:

- Activity is essential for plant safety: Activities related to ensuring the safety of personnel, equipment, and processes within the manufacturing operation.
- Activity is essential for plant reliability: Activities focused on maintaining the reliability and availability of equipment, minimizing downtime, and preventing failures.

- Activity is essential to plant efficiency: Activities aimed at improving operational efficiency, reducing waste, optimizing resource utilization, and enhancing overall productivity.

- Activity is essential to product quality: Activities that ensure the production of high-quality products, including quality control, inspection, and adherence to quality standards and specifications.

- Activity is essential to maintaining regulatory compliance: Activities that ensure compliance with applicable regulations, standards, and legal requirements governing the manufacturing process.

The ISA 95 standard emphasizes the integration of enterprise-control systems and provides models and terms to facilitate this integration. Information sharing between Level 4 (business planning and logistics system) and Level 3 (manufacturing operations system) is crucial and involves four main types of information:

- Operational status and scheduling data: Information about the current status of operations, production schedules, resource availability, and planned maintenance activities.

- Product genealogy and tracking information: Information that tracks the genealogy and history of products, including raw materials used, production processes applied, and any transformations or changes throughout the manufacturing process.

- Product quality requirements and test results: Information related to product quality specifications, testing procedures, test results, and quality control measures implemented to ensure product conformity.

- Compliance requirements: Information pertaining to regulatory compliance requirements, including environmental regulations, safety standards, and industry-specific regulations that need to be followed during the manufacturing operations.

By sharing these types of information, effective coordination, decision-making, and optimization can be achieved between the business planning and logistics system (Level 4) and the manufacturing operations system (Level 3).

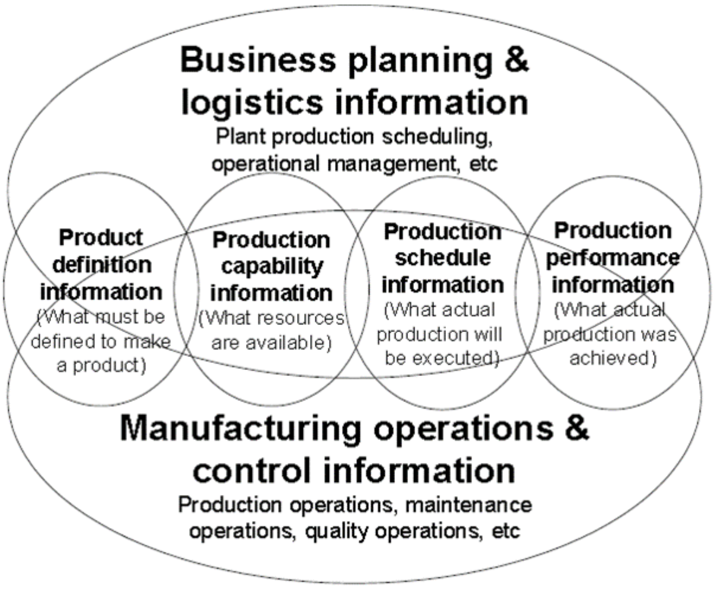

Figure 20 Categories of information exchange. (ANSI/ISA-95.00.03-2005).

The requirements for Maintenance Operations Management, Production Operations Management, Quality Operations Management, and Inventory Operations Management can be met by the same information layout of the production system as shown in the previous figure. This layout allows for effective information exchange and coordination between these different components of Manufacturing Operations Management.

In the following figure, Production Operations Management is depicted as sharing information related to the production schedule, product definition, production performance, and production capability. This information exchange enables efficient planning and execution of production activities.

Similarly, Maintenance Operations Management, Quality Operations Management, and Inventory Operations Management also have their own information exchange layouts. These layouts facilitate the sharing of critical information specific to each component, such as maintenance schedules, quality requirements and inspection results, and inventory levels and movements.

The information sharing between these different components of Manufacturing Operations Management is vital for the overall success of manufacturing operations. It enables effective coordination, optimization, and decision-making across maintenance, production, quality, and inventory management functions. By having a unified information layout, the different components can access and utilize the necessary data to ensure smooth and efficient operations.

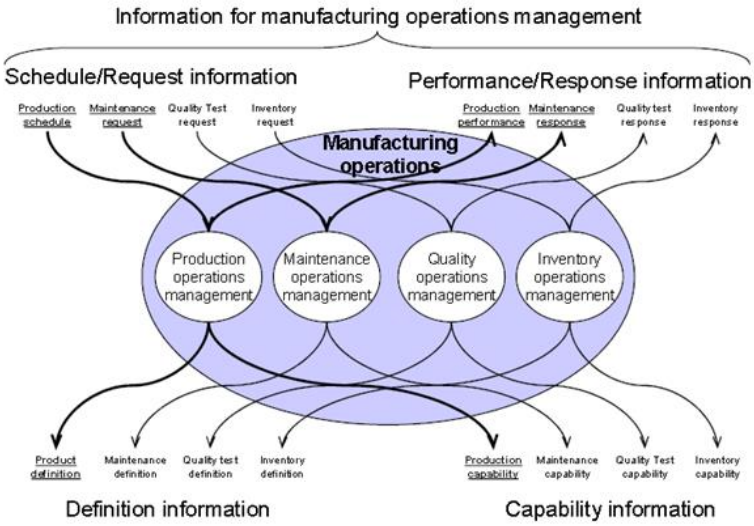

Figure 21 Manufacturing operations information. (ANSI/ISA-95.00.03-2005).

Generic Activity Model

ISA-95 standard part 3 focuses on the activities within manufacturing operations management (MOM) at level 3 of the functional hierarchy model. MOM involves organizing and coordinating various tasks and responsibilities related to workforce, materials, equipment, and energy to transform raw materials or components into finished products. These activities are typically carried out by the work force, equipment, and information systems, which work in collaboration and exchange information with both higher-level functions at level 4 and lower-level functions at level 2. The seamless exchange of information allows for effective coordination and integration of operations across different levels of the hierarchy.

The main types of activities within MOM are:

- Production Operations Management: This involves planning, scheduling, and executing production processes to meet production targets, optimize resource utilization, and ensure timely delivery of products. It includes activities such as production planning, job scheduling, routing, and monitoring of production progress.

- Maintenance Operations Management: This focuses on managing the maintenance activities of equipment and facilities to ensure their optimal performance, minimize downtime, and extend their operational lifespan. It includes activities such as preventive maintenance scheduling, equipment inspections, repairs, and maintenance record keeping.

- Quality Operations Management: This encompasses activities related to ensuring product quality and compliance with specified standards and requirements. It involves quality control, inspection, testing, and analysis of production processes and products to identify and address any deviations or non-conformities.

- Inventory Operations Management: This involves managing and controlling the inventory of raw materials, components, and finished products. It includes activities such as inventory tracking, stock replenishment, material handling, and inventory optimization to balance supply and demand and minimize inventory holding costs.

These MOM activities are critical for efficient and effective manufacturing operations. They enable organizations to optimize resources, maintain product quality, meet production targets, and ensure smooth operations throughout the manufacturing process. By implementing effective MOM practices, companies can enhance their productivity, reduce costs, and improve customer satisfaction.

The standard uses a hierarchical form for operations management, where each category consists of multiple activities with defined duties and tasks. The generic activity model follows a demand-reply data flow cycle, starting with request data and progressing through detailed scheduling, work dispatching, execution management, data collection, and response generation. Feedback from level 3 activities informs the status and progress of each category. This cycle is driven by analysis to improve, correct, and optimize work. The model encompasses resource management, work definition management, and provides a framework for planning, managing, and executing work.

Figure 22 Generic Activity model of manufacturing operations management. (ANSI/ISA-95.00.03-2005).

This generic model serves as a framework for designing manufacturing information systems, outlining the flow of data within the system. It involves analyzing each task, from input capture to data processing and output of results. The generic structure does not represent the true execution of a manufacturing information system, but it provides a reliable outline for such systems. The goal of a generic activity model is to figure out how data might flow through the manufacturing operations system. This involves analyzing each task involved in the system, starting from the capture of input information and resources, through the calculation and processing of data, to the output of results. The main activities are represented by ovals, and the lines with arrowheads depict the flow of data between these activities.

Equipment hierarchy model

The standard categorizes the enterprise's main physical assets that are used in manufacturing based on their functionality, location, performed activities, and any associations with similar resources. Overall, this hierarchy model provides a structured framework for organizing and managing manufacturing operations. It ensures clear roles and responsibilities at each level, enabling effective decision-making, resource allocation, and performance optimization throughout the production process. The equipment hierarchy model, illustrated in the following figure.

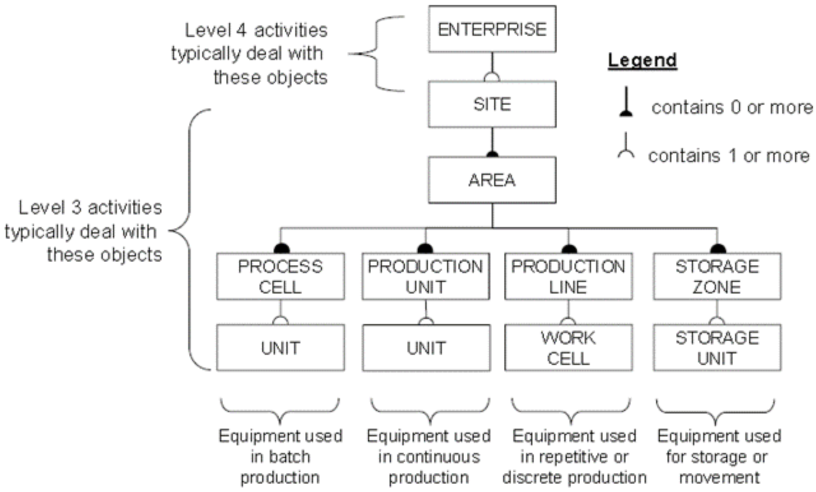

Figure 23 Typical Equipment Hierarchy. (ANSI/ISA-95.00.03-2005).

Enterprise: At the Enterprise level, the focus is on high-level decisions and strategies regarding the final products, manufacturing locations, and production methods. It involves the coordination of multiple locations and areas to ensure quality, cost-effectiveness, and timely delivery of products and services. The Enterprise level is responsible for setting overall goals and objectives for manufacturing operations.

Site: The Site level represents physical locations or geographical classifications within the Enterprise. Sites are identified based on their specific production capabilities and resources. They serve as operational units responsible for managing and optimizing production processes. Level 4 activities, such as management and optimization, are associated with Sites to maximize efficiency and performance.

Area: Areas are further subdivisions within Sites, typically organized based on physical or site-specific classifications. They consist of work centers and work units, which are the lower layers of the hierarchy. At the Area level, Level 3 activities are performed, which involve specific tasks and processes related to production operations.

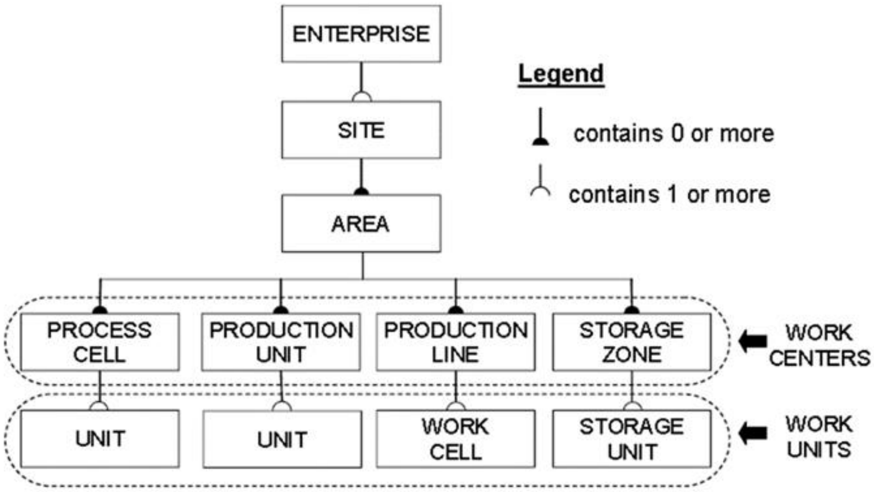

Figure 24 Work centers and work units. (ANSI/ISA-95.00.03-2005)

Work Center: Work Center: Work centers are equipment elements that are classified within an area in the manufacturing operations management hierarchy. The standard provides specific terminology for work centers in manufacturing operations management, which are involved in discrete, batch, and continuous processing, as well as storage and material movement activities.

According to the standard, work centers can be categorized into different types based on their specific functions in the manufacturing process:

- Batch Production: Work centers involved in process cells dedicated to batch production.
- Continuous Production: Work centers operating within production units for continuous production.
- Discrete Production: Work centers integrated into production lines for discrete production.
- Storage: Work centers designated for storage or movement activities within storage zones.

A work center can consist of one or more work units, which are responsible for carrying out specific tasks within the work center. This classification provides a standardized framework for defining and understanding the different types of work centers in manufacturing operations management.

Work Unit: Work Unit: Work units are equipment elements that exist at the lowest layer within the role-based equipment hierarchy, positioned under a work center. Work units are typically scheduled and managed by level three functions in manufacturing operations management. According to the standard, there are three primary types of work units:

- Batch and Continuous Production: Work units specifically designed for executing tasks related to batch or continuous production processes. These work units are responsible for carrying out production activities in a controlled and efficient manner.

- Discrete Production: Work units known as work cells that are dedicated to discrete production processes. These work cells are typically configured to handle specific tasks or operations in the production line, focusing on the assembly or processing of individual items or components.

- Storage Unit: Work units assigned to storage or material movement functions within the manufacturing facility. These work units are responsible for storing, organizing, and transporting equipment, spare parts, raw materials, or finished products as required by the production operations.

By categorizing work units into these distinct types, the standard provides a clear framework for understanding their specific roles and responsibilities within the manufacturing operations management hierarchy.

Storage Zone and Storage Units:

Storage Zone: A storage zone is a designated area within a manufacturing facility that possesses the necessary capabilities to receive, store, move, and ship various items such as equipment, spare parts, raw materials, and final products. It serves as a centralized location for inventory management and control. In addition to internal material transport between work centers within the same enterprise, a storage zone may also facilitate the movement of materials between different enterprises or external entities. Storage zones can encompass various types of storage areas, such as:

- Warehouse: A warehouse is a common type of storage zone that is typically used for storing finished products, raw materials, or intermediate goods. It provides a controlled environment for inventory management and may include shelves, racks, or other storage systems.

- Tank Farm: A tank farm is a storage zone specifically designed for bulk liquid storage, such as petroleum products, chemicals, or gases. It consists of multiple tanks or vessels that allow for the safe and organized storage of these substances.

- Holding Area: A holding area refers to a temporary storage zone where materials or products are held for a short period before being processed, transported, or further distributed. It provides a buffer between different stages of the production or supply chain.

- Silo Farm: A silo farm is a storage zone primarily used for storing granular or powdered materials, such as grains, cement, or powders. Silos are tall, cylindrical structures that can hold a large volume of material and provide protection from environmental factors.

These different types of storage zones cater to specific storage requirements and are tailored to the nature of the materials or products being stored. They play a crucial role in ensuring efficient inventory management and smooth flow of materials within the manufacturing operations management framework.

Storage Units: Storage units are specific business systems or components that are responsible for maintaining inventory at a more detailed level than a storage zone. They are designed to manage and track inventory items with greater precision and granularity. The physical location of a storage unit may vary depending on the nature of the final product or the specific requirements of the manufacturing operations.

Storage units are the smaller components within a storage zone that are used to organize and store individual items. They can vary depending on the type of material being stored and the specific requirements of the storage zone. Here are some examples of storage units:

- Rack, Bin, Slot: These storage units are commonly used in warehouses or storage facilities to store smaller items or components. Racks provide shelves or compartments where bins or slots can be placed to organize and store items efficiently.

- Tank, Pipe Section: In storage zones such as tank farms or facilities that handle liquids or gases, tanks and pipe sections are used as storage units. Tanks are large containers that hold liquids, while pipe sections are used for storing or transporting liquids or gases through a piping system.

- Pallet, Barrel, Container: Pallets, barrels, and containers are commonly used storage units for handling and storing a variety of materials. Pallets are flat structures used for stacking and transporting goods. Barrels are cylindrical containers typically used for liquids or bulk materials. Containers come in various sizes and shapes, providing a versatile storage solution for different types of goods.

- Silo: Silos can also be considered storage units, particularly in the context of storing granular or powdered materials. Similar to tanks, silos are tall structures used for storing bulk materials.

  These storage units help organize and manage inventory within storage zones, ensuring proper allocation, easy retrieval, and efficient utilization of materials in manufacturing operations management.

By distinguishing between storage zones and storage units, the standard provides a framework for effective management of inventory and material handling within manufacturing operations management. Storage zones offer a broader perspective, while storage units enable more specific and detailed inventory control, ensuring efficient storage, retrieval, and movement of materials throughout the production process.

The classification of zones of responsibility in the equipment hierarchy provides a framework for understanding the different levels of functions within the manufacturing operations management (MOM) system. While each level has its primary focus, it's important to recognize that there can be overlap and interaction between the levels based on specific requirements and circumstances.

At the highest level, level 4 functions are primarily concerned with enterprise-wide planning and strategic decisions. This includes defining the overall goals and objectives of the organization, determining the products and markets, and establishing policies and standards. However, certain level 4 functions may extend into the activities within an area or work center when necessary. This flexibility allows for coordination and alignment between different levels of the hierarchy.

Level 3 functions are typically carried out within a specific area and its associated work centers and work units. These functions are more operationally focused and involve activities such as production scheduling, resource allocation, and process optimization. While level 3 functions are primarily executed within the designated area, they may need to collaborate and coordinate with level 4 functions to fulfill their responsibilities effectively.

It's important to note that the boundaries between the levels are not rigid, and there can be fluidity and interaction between them. Functions at different levels may overlap, and their activities can impact and influence each other. This highlights the interconnected nature of manufacturing operations management and the need for collaboration and communication across different levels to ensure efficient and effective operations.

Activity models for Production, Maintenance, Quality and Inventory operations management

The activity model of manufacturing operations management consists of various interconnected activities that collaborate to achieve operational efficiency. These activities involve specific duties and tasks that depend on the specific requirements of the operation. Information flows (between levels 1, 2 and 3) serve as the connecting link between these activities, facilitating the exchange of relevant information.

The key information exchanged between the activities includes:

- Definition: This information describes the operations to be performed and the resources needed to carry them out effectively.
- Capability data: This refers to information about the properties and capabilities of the resources involved in the manufacturing process.
- Schedule/request information: This information pertains to the scheduling and execution of operations, including the allocation of resources and the sequencing of tasks.
- Performance-response information: This includes feedback on the performance and results of the manufacturing operations, providing insights into the effectiveness and efficiency of the processes.

By leveraging this operational and exchanged data, manufacturing operations management can ensure that operations are performed according to defined specifications, utilize available resources optimally, adhere to schedules, and achieve desired performance outcomes. The continuous exchange of information supports informed decision-making and enables adjustments and optimizations as needed to enhance overall manufacturing operations.

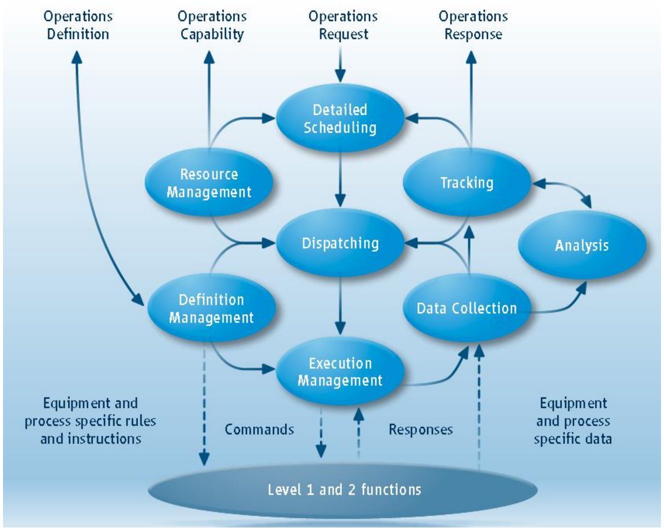

Figure 25 Generic Activity model of manufacturing operations management extended by the process interfaces. (German Electrical and Electronic Manufactures‘ Association, 2011)

The group of activities designated as the major functions are represented by the oval shapes of the manufacturing operations management generic activity model. The data and information flow pathways between the activities are represented by lines with arrowheads. The fact that any firm could have a different organizational structure is fairly simple to describe and comprehend.

As a result, the generic model only gives information on what will be done and the roles associated with the activities, not on how they will be structured and carried out. It outlines what should be done, not how it should be set up. Role assignments and arrangements for labor employees or systems may vary among organizations.

Resource Management	Resource management in manufacturing operations management (MOM) involves the effective management of information related to distributed resources that are crucial for the functioning of the manufacturing process. This information encompasses various aspects of resource management, including capacity, allocation, and availability. This information enables planners and managers to make informed decisions regarding production scheduling, resource utilization, and optimization, ultimately contributing to efficient and effective manufacturing operations.
Definition management	Definition management in Manufacturing Operations Management (MOM) refers to the process of establishing and managing the definitions, processing instructions, rules, and requirements associated with various functions within MOM. It involves documenting and maintaining clear and consistent definitions for the manufacturing processes, operations, and related activities.
Detailed Scheduling	For Manufacturing Operations Management (MOM) functions, detailed scheduling combines the tasks that go into making time-related demands and sequences to make the best use of local or distributed resources. To ensure the most effective use of resources and a successful production process, businesses need to constantly monitor their resource capacity, allocation, and availability

Dispatching	Dispatching activities in Manufacturing Operations Management (MOM) involve managing, coordinating, and overseeing manufacturing operations. These activities include handling schedules and coordinating the use of individual resources, which are created during the detailed scheduling process. Dispatching ensures that resources are allocated effectively and that production tasks are carried out according to the established schedules.
Execution Management	Execution management plays a crucial role in overseeing and enhancing the production process by ensuring compliance with schedules, orders, and company policies. It involves coordinating dispatching activities, monitoring resource capacity, allocation, and availability to ensure smooth and efficient production operations. By effectively managing execution, businesses can optimize their production processes and achieve better results.
Data Collection	Data collection in Manufacturing Operations Management involves the acquisition, processing, and management of data from various processes, primarily at levels 1 and 2. This data can originate from user inputs, actions, or measurements, either directly or indirectly through events. It may be collected periodically or on-demand, and its context, including timestamps, is crucial for accurate evaluation. To ensure the usefulness of the data, it is essential to identify its source accurately and record the associated context information.
Tracking	Tracking in Manufacturing Operations Management involves capturing and monitoring information from various processes and functions at level 4. This includes data generated from user-initiated inputs and actions, which can provide valuable insights into the different aspects of manufacturing operations management. By tracking this information, businesses can gain visibility into their processes, identify trends, and make informed decisions to optimize their operations.
Analysis	Absolutely, understanding the context of data collection is crucial for accurate and meaningful analysis in Manufacturing Operations Management. The context includes information such as the time and

location of data collection, the specific processes or activities being measured, the operational conditions, and any relevant variables or factors that may impact the data. By considering the context, businesses can ensure that the evaluation and reporting of performance data are accurate, relevant, and reliable. This information can then be used to make informed decisions, identify areas for improvement, and optimize business systems and processes.

Model of production operations management activity

The model of production operations management activity defines various activities and their associated roles in the production process. It is important to note that these activities do not necessarily refer to specific systems, software, or personnel. Instead, they serve as a framework to identify potential activities and the roles involved in each activity.

Production requests and production responses are integral to manufacturing operations management. While production plans may drive production operations, manufacturing operations management utilizes production requests and responses to handle rework, local intermediate product production, consumables, and more.

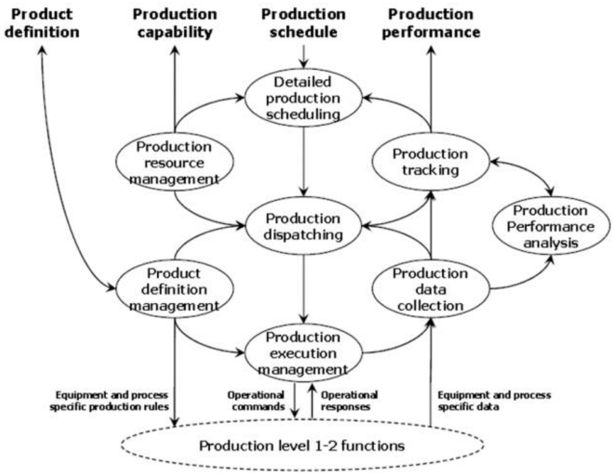

Figure 26. Generic Activity Model of Production Operations Management, (ANSI/ISA-95.00.03-2005)

Equipment and process specific production rules are defined as specific instructions sent to Level 2 based on assigned tasks. These rules ensure that equipment and processes adhere to the required specifications.

Operational commands are requests sent by Level 2. These commands typically instruct the start or completion of specific elements within a work order.

Operational responses are the information received from Level 2 in response to the commands. These responses typically indicate the completion or status of work order elements.

Equipment and process specific data refer to information obtained from Level 2 monitoring. This includes data about the running processes and the associated resources. It is important to collect and store this data for future analysis and optimization of performance.

Production Resource Management Production Resource Management is a crucial aspect of production operations, involving the management of resources necessary for the production process. The goal of resource management is to effectively utilize these resources to deliver the final product.

Collecting and storing data related to the resources involved in the production process plays a vital role in identifying potential performance issues and optimizing resource utilization. By analyzing this data, organizations can pinpoint areas where inefficiencies occur and make informed decisions to enhance resource allocation and improve overall production efficiency.

The data collected can provide valuable insights into resource availability, utilization rates, downtime, maintenance requirements, and other key performance indicators. This information enables organizations to identify bottlenecks, plan for resource capacity, optimize scheduling, and implement strategies to maximize resource utilization.

Ultimately, through effective resource management and data-driven optimization, organizations can streamline their production processes, reduce costs, minimize waste, and enhance overall operational efficiency.

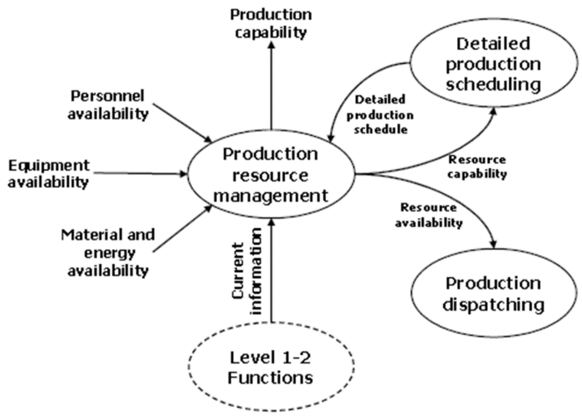

Figure 27. Production resource management activity model interfaces (ANSI/ISA-95.00.03-2005).

Product Definition Management Product Definition Management involves controlling and managing product-related information, including functions and manufacturing processes. It ensures consistency and accuracy in product definitions and follows the ANSI/ISA-95.00.03-2005 standard. It facilitates effective communication, collaboration, and regulatory compliance throughout the product lifecycle, leading to improved efficiency and product quality. It involves establishing and maintaining a centralized repository of product-related information, which serves as a single source of truth for all stakeholders involved. The ANSI/ISA-95.00.03-2005 standard provides guidelines and best practices for controlling and managing product definitions effectively. By implementing sound product definition management practices, organizations can enhance efficiency, reduce errors and rework, improve product quality, and accelerate time-to-market for new products.

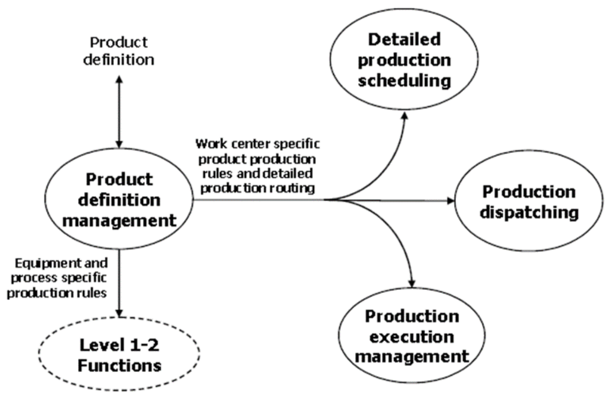

Figure 28.Product definitions, management activities, and interfaces. (ANSI/ISA-95.00.03-2005).

Detailed production scheduling Detailed production scheduling involves organizing production equipment, with optimized schedules. It takes into account parameters like batch size, setup time, resource availability, and utilization. Resource availability may need to be defined within the schedule. The goal is to create an efficient production schedule that maximizes the performance of each machine and plant, while ensuring they operate within their optimal parameters. By considering these variables, production can be effectively managed and optimized.

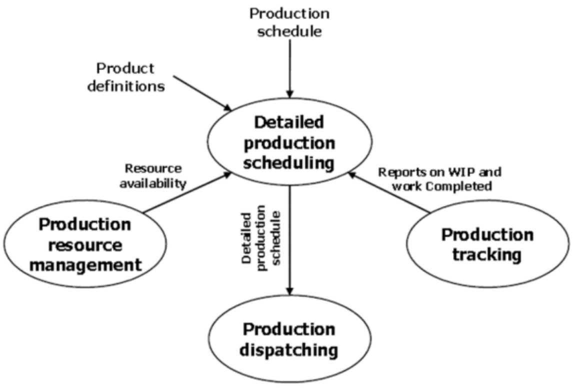

Figure 29. Detailed production scheduling activity model interfaces (ANSI/ISA-95.00.03-2005).

Production dispatching. Production dispatching involves the control of the production process by breakdown equipment and personnel. This includes tasks like scheduling batches and issuing work orders through a batch control system. The process is facilitated by utilizing various resources such as material requirements planning (MRP) systems, computer-aided design (CAD) systems, Enterprise Resource Planning (ERP) systems, and manufacturing execution systems (MES). These systems help in organizing and coordinating the production activities to ensure efficient utilization of resources and timely execution of work orders.

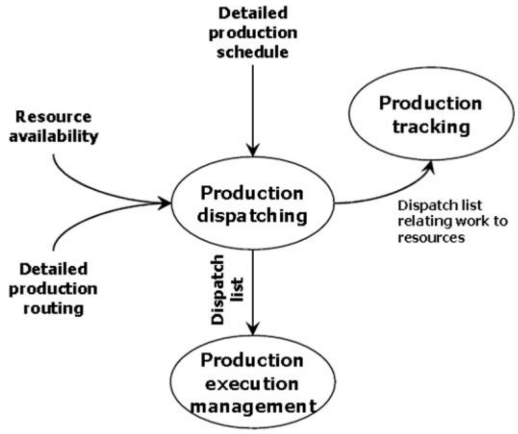

Figure 30.Production dispatching activity model interfaces (ANSI/ISA-95.00.03-2005).

Management of Production Execution Production execution management involves carrying out the production process based on product definitions and manufacturing instructions. It includes selecting and initiating production steps and managing the transition between different steps. During this process, data on materials used and processing time is collected, providing information on the order status and current progress. This information allows for local optimization of production steps, resulting in shorter production times and reduced material and resource usage. By optimizing production at each step, overall efficiency and resource utilization can be improved.

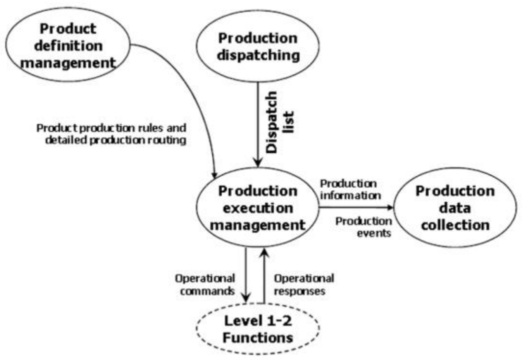

Figure 31.Production execution management activity model interfaces (ANSI/ISA-95.00.03-2005).

Production Data Collection Production data collection involves gathering relevant data during the production operation or individual steps. This includes capturing sensor values, status information, transaction results, and model evaluations related to production. The collected data is then utilized to generate reports, alerts for operators, and provide valuable information for managerial decision-making. This information aids in process control, identifying maintenance needs, scheduling resources, and optimizing production capacity. By leveraging the collected data, organizations can gain insights into their production processes and take proactive measures to enhance efficiency and productivity.

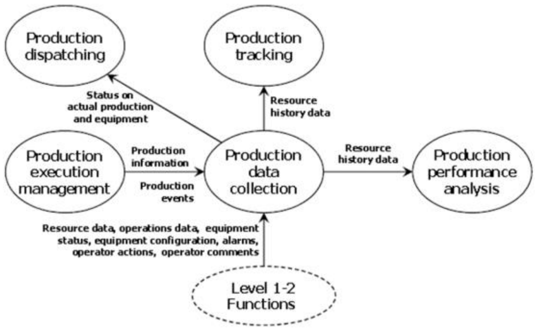

Figure 32.Production data collection activity model interfaces (ANSI/ISA-95.00.03-2005).

Production Tracking. Production tracking is the process of collecting and analyzing data related to the resources utilized in production, including personnel, production equipment, materials consumed and produced, costs, and performance analysis results. The information gathered through production tracking is then used to update and optimize detailed production schedules. By closely monitoring production operations, manufacturers can enhance the efficiency and accuracy of their scheduling processes, leading to improved overall productivity and performance.

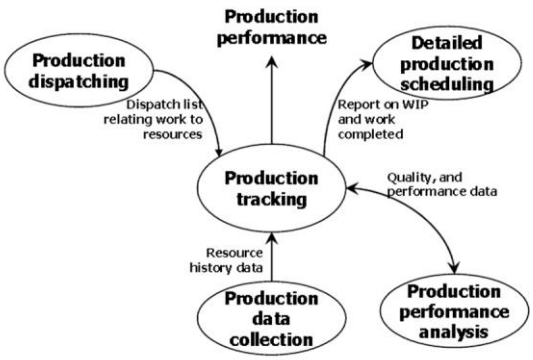

Figure 33. Production tracking activity model interfaces. (ANSI/ISA-95.00.03-2005).

Analysis of production performance Production performance analysis focuses on evaluating various aspects of production, such as cycle times, equipment utilization, facility load, procedure effectiveness, and production variability. By analyzing these factors, key performance indicators (KPIs) can be calculated to assess the efficiency and effectiveness of production processes. The optimization of production performance involves identifying areas for improvement and implementing strategies to enhance productivity and resource utilization.

The analysis and optimization of production performance are continuous processes that run parallel to ongoing production activities. As market or environmental conditions change, or when new constraints are introduced, it may be necessary to reanalyze, adjust policies, and optimize production operations accordingly. Efficient and effective management of resources is crucial to achieving optimal production performance.

By continually monitoring and optimizing production performance, organizations can strive for increased productivity, reduced costs, improved quality, and enhanced overall operational efficiency.

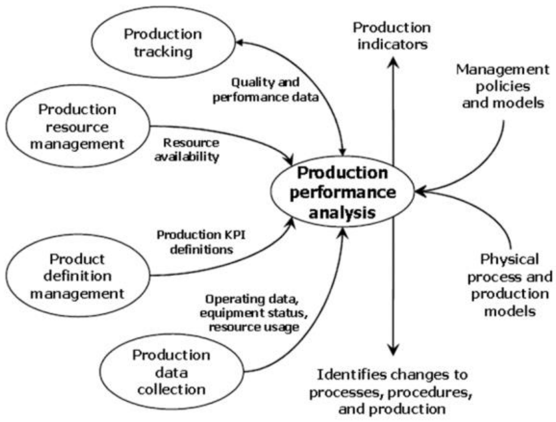

Figure 34.Production performance analysis activity model interfaces (ANSI/ISA-95.00.03-2005)..

Model of maintenance operations management activity

The model illustrated in Figure 36 depicts activities related to maintenance tasks and the flow of information among these activities. It outlines the primary maintenance tasks and highlights how information is communicated and shared between them.

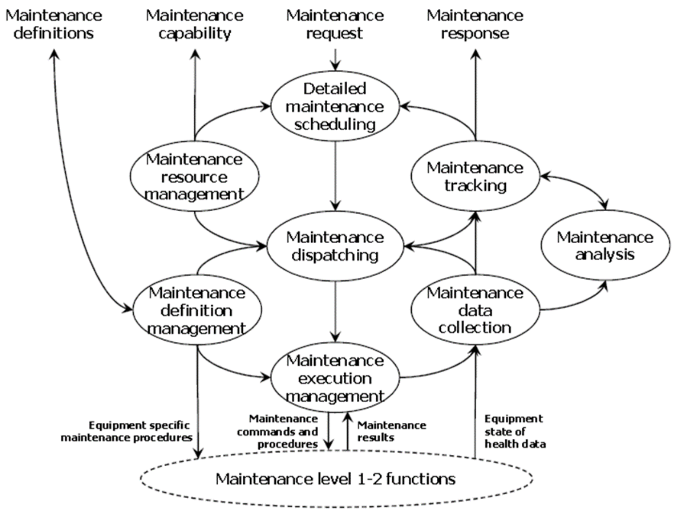

Figure 35. Generic Activity Model of Maintenance Operations Management, (ANSI/ISA-95.00.03-2005)

To ensure efficient maintenance operations management, it is essential to define equipment-specific maintenance procedures. These procedures consist of specific instructions tailored to the equipment and are communicated to Level 2 based on assigned tasks. In addition to equipment-related tasks, maintenance procedures may encompass maintaining an appropriate environment for the processes. Having accurate information and well-defined procedures is crucial for proper maintenance operations and ensuring optimal equipment performance.

Maintenance commands and procedures refer to the requested information transmitted to Level 2, outlining the necessary instructions to execute a particular maintenance task. These commands may contain comprehensive maintenance documentation, specifying the required work specifications. They can be assigned to individuals with instructions or devices equipped with relevant information for proper handling. To ensure that maintenance operations are effective and efficient it is crucial to have accurate information, well-defined procedures, and appropriate resources readily available. This enables the smooth execution of maintenance tasks, resulting in optimal outcomes.

Maintenance results encompass the information received from Level 2 as a response to maintenance commands and procedures. These results typically indicate the fulfillment of the assigned maintenance tasks. They may consist of detailed data regarding the activities performed during the maintenance process. To effectively utilize the information, procedures, and resources in place, it is crucial to establish an analysis and feedback system. This system facilitates the evaluation of maintenance outcomes, identification of improvement opportunities, and the provision of feedback for continuous enhancement of maintenance operations.

Equipment state of health data refers to information obtained from Level 2 or Level 1 monitoring, indicating the condition of the equipment. This data can encompass historical, current, or predictive information regarding the equipment's state. It is distinct from maintenance commands or procedures. To effectively utilize this data, it is important to implement a system of analysis and feedback. This system enables thorough examination of equipment conditions, identification of trends, potential issues, and provides valuable feedback for informed maintenance decisions and proactive maintenance practices

Management of Maintenance Resources. Maintenance Resource Management encompasses the information and resources necessary for conducting maintenance work effectively. This includes standard and specialized tools, both internal and external personnel, maintenance documentation, and spare parts and consumables.

The state of resources encompasses various aspects related to the equipment being maintained. This includes factors such as the health status, capabilities, availability, expected utilization, location, and location accessibility of the equipment. Evaluating the health status involves assessing the overall condition of the equipment and identifying any potential issues or maintenance needs. Understanding the capabilities of the equipment helps determine its capacity and performance capabilities during maintenance activities. Availability refers to the equipment's availability for maintenance, considering factors such as production schedules and operational requirements. Expected utilization involves estimating the level of utilization or usage of the equipment during maintenance activities. The location and location accessibility of the equipment are important considerations to ensure proper planning and logistics for maintenance operations.

Additionally, it is necessary to consider whether the maintenance work can be conducted while the equipment is in operation or if a complete shutdown is required. This assessment depends on the nature of the maintenance task, the potential impact on operations, and the safety requirements. By carefully considering these factors, organizations can effectively plan and manage maintenance activities while minimizing disruptions to ongoing operations.

Within the Maintenance Definition Management process, instructions and definitions for performing maintenance are defined and managed. This process requires resources from both inside and outside the organization, such as standard tools, personnel resources, maintenance documentation, spare parts, and consumables.

Maintenance Dispatching. Maintenance dispatching involves the issuance of maintenance orders to relevant personnel, considering their availability and capacities both within and outside the organization This process is critical for the timely and effective performance of maintenance, as it ensures that the necessary personnel are available to carry out the maintenance tasks.

Management of Maintenance Execution. Maintenance Execution Management involves monitoring and overseeing the implementation of maintenance orders. It ensures that maintenance and repair instructions, regulations, and quality standards are followed, and that proper documentation is maintained for the condition and outcomes of the maintenance tasks. The management also oversees the monitoring and utilization of appropriate certificates for equipment, spare parts, tools, and personnel during the dispatching process.

Maintenance Data Collection. Maintenance Data Collection involves gathering and recording data generated during the execution of maintenance orders. This includes capturing information about the current state of the equipment being serviced or repaired, feedback and any cost incurred by both internal and external resources. The collected data is integrated into the specific equipment maintenance log enabling tracking of any changes or trends in the maintenance process. By leveraging this data, organizations can gain insights into the efficiency and effectiveness of their maintenance operations and make informed decisions for process improvement and optimization.

Maintenance Tracking. Maintenance Tracking involves monitoring and recording information on the operation of resources during maintenance, as well as the effectiveness of maintenance outcomes. This includes maintaining datasets and logs on the condition and usability of serviced equipment. The collected information is important for demonstrating compliance with regulations and standards. This data can then be used to track any changes or trends in the maintenance process and can provide valuable insight into how well the maintenance is being performed, allowing managers to identify any areas of improvement and ensure they are meeting all applicable standards.

Maintenance Analysis. Maintenance Analysis involves evaluating the costs associated with personnel, spare parts, auxiliary equipment, and various direct and indirect expenses within maintenance processes. The objective is to identify problem areas and potential areas for optimization to achieve additional improvements. The primary focus is on optimizing the maintenance strategy and maximizing the return on assets (ROA). The analysis results can serve as feedback for production scheduling and can be used to calculate maintenance performance indicators, which assess the effectiveness of maintenance activities. The findings and outcomes of maintenance analysis provide valuable decision support to improve overall operational efficiency. This information enables informed decision-making and strategic planning to enhance the efficiency of maintenance operations, minimize downtime, improve asset reliability, and ultimately drive greater overall operational efficiency. By assessing maintenance performance indicators, organizations can determine how well they are optimizing their maintenance strategy and make necessary adjustments to maximize ROA (return on assets).

Quality operations management activity model

The model depicted in Figure 32 showcases the activities associated with inspections or testing operations. This model outlines the required quality testing tasks and their sequential order of execution. It doesn't say how those tasks should be done within a certain organizational structure. In other words, the model outlines the logical flow of quality activities related to inspection or testing operations but does not specify how those tasks are to be executed and managed.

In the activity model for quality test operations, it is not necessary for quality requests and feedback to always flow between Level 3 and Level 4. Quality test requests are often generated internally within Level 3 systems. These requests and corresponding responses can be exchanged individually or in groups. A collection of organized requests can be referred to as a quality test schedule, while a collection of organized responses can be considered as the performance of the quality test.

Quality test operations within the model must therefore account for both the generation of quality requests and feedback within Level 3 systems, as well as those that may cross between Level 3 and Level 4.

Figure 36. Generic Activity Model of Quality Test Operations Management, (ANSI/ISA-95.00.03-2005)

Quality parameters and procedures are instructions sent to Level 2 and Level 1. They may include standard operating procedures or calculations. To ensure accuracy and consistency, feedback should be obtained from all relevant sources

Test commands are requests sent to Level 2 or Level 1, providing information about the test to be conducted or instructions to control equipment.

Test responses are the information received in response to test commands from Level 2 or Level 1. They can include test results or signals indicating the status of sensors or equipment.

Quality-specific data is obtained from Level 2 or Level 1 and includes operational data, often with contextual information. This data helps interpret test responses and make informed decisions.

Management of Quality Test Resources. Quality Test Resource Management specifies the staff qualifications , materials, and equipment that are required for carrying out quality tests.

Management of Quality Test Definition. The management of quality test definition involves the process of establishing and overseeing personnel qualifications, quality testing procedures, and work instructions for carrying out these procedures. It encompasses defining the necessary skills and qualifications of personnel involved in quality testing, establishing the procedures to be followed for conducting quality tests, and providing detailed work instructions for executing these procedures. Additionally, it includes determining the frequency at which tests should be performed and specifying the methodology to be employed during the testing process.

Detailed quality test scheduling. Detailed quality test scheduling pertains to the meticulous planning of quality tests, whether they are conducted as part of the production processes or separately. It involves considering factors such as the availability of test systems and personnel, as well as scheduling test preparation and evaluation activities. This ensures that quality tests are properly organized and executed within the designated timeframes.

Quality test dispatch. Quality test dispatch refers to the process of issuing test orders or samples to the quality control department in accordance with established procedures and plans. This ensures that the necessary tests are carried out in a timely manner and in accordance with the designated protocols.

Quality test execution management. Quality test execution management involves the execution of quality tests and the effective control and monitoring of resources, including equipment, materials, and personnel. It also encompasses ensuring adherence to quality standards, product datasheets, and specifications throughout the testing process. This ensures that the tests are conducted accurately and in line with the required quality parameters and specifications.

Quality Test Data Collection. Quality test data collection involves gathering and compiling different types of data associated with the testing process. This includes the actual test data, execution data, user input during testing, intermediate data, and data presented in test reports. By collecting and analyzing this information, organizations can evaluate the test results, track progress, and make informed decisions to enhance quality and performance.

Tracking of Quality Tests. Quality test tracking is responsible for providing feedback on quality to the relevant functions in levels 3 and 4. It involves compiling test results into comprehensive test reports that contain all pertinent information. These reports can be generated on demand or at specific production stages or milestones. Different sets of test reports can be issued at various stages of the process and for different units, ensuring thorough monitoring and evaluation of quality throughout the testing process.

Quality performance analysis. Quality performance analysis focuses on evaluating the results and performance of quality tests to drive improvements in product quality. It is an ongoing process that involves analyzing quality deviations, and testing of effectiveness, and resources. Additionally, it includes identifying trends in important quality indicators, investigating the root causes of quality problems, and implementing corrective actions. The ultimate objective is to enhance the overall quality state of the product until the desired outcome is achieved.

Model of inventory operations management activity

The model depicted in Figure 38 outlines the inventory management activities associated with the transfer of materials between different work centers. While this model illustrates the sequential order of transfer activities, it does not specify how these activities should be executed within a particular organization structure. The following Figure 38 provides an overview of the basic information flows between these activities.

To ensure effective movement and control, inventory storage definitions should be configured to transmit relevant information to Level 2 from storage definition data.

Inventory commands refer to requests to level 2, primarily concerning the movement or transfer of items.

Inventory replies represent the feedback consigned by level 2 as a reply to inventory orders.

Inventory-specific data encompasses information about equipment involved in inventory functions, details about the information and materials (location quantity specifics characteristics, which is received from level 2.

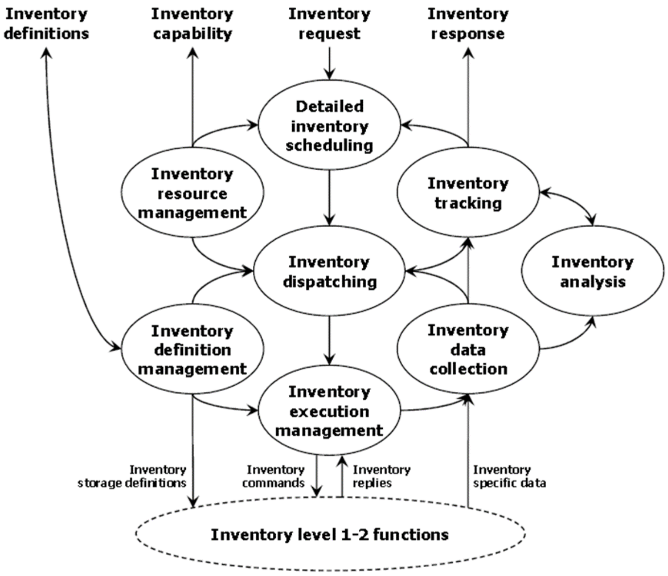

Figure 37. Generic activity model of inventory operations management. (ANSI/ISA-95.00.03-2005).

Inventory resource management involves the management of various resources associated with inventory and material movement processes. This includes managing personnel resources, such as their skills, experience, and certifications, to ensure efficient handling and management of inventory. Additionally, consumables, spare parts, and energy resources are considered as part of inventory resource management.

Inventory definition management encompasses activities focused on specifying and managing storage and transportation instructions for materials. This includes defining parameters related to inventory levels, shipping instructions, and resource utilization within the warehouse. The purpose of inventory definition management is to establish clear guidelines and instructions for handling materials, ensuring proper storage, and facilitating efficient transportation. By effectively managing inventory definitions, organizations can streamline their warehouse operations, optimize resource utilization, and enhance overall inventory management processes.

Detailed inventory scheduling involves collecting information on inventory levels and material movements. It includes tasks such as inventory tracking, resource planning, and optimizing transportation processes. The aim of detailed inventory scheduling is to effectively manage inventory by ensuring appropriate stock levels, optimizing resource allocation, and improving transportation efficiency.

Inventory dispatching involves the issuance of orders to control and update stock levels based on predefined definitions and schedules. It includes activities such as order processing, stock allocation, and fulfillment. The goal of inventory dispatching is to ensure that the right products are available in the right quantities at the right time to meet customer demands while minimizing stockouts and excess inventory.

Inventory execution management involves overseeing warehouse-related tasks to ensure the proper utilization of storage, transportation, and personnel resources in accordance with established procedures and quality standards. It includes monitoring and accounting for stock levels and generating reports to track inventory status. By effectively managing inventory execution, organizations can maintain operational efficiency, ensure compliance, and have accurate visibility into their stock.

Inventory data collection involves gathering information about stock-related activities, processed materials, product tracking, storage status, equipment utilization, warehouse and transportation operators, quality tracking, and maintenance tracking. This data is crucial for regulatory compliance, optimizing material flow, reducing waste, and improving efficiency in inventory management.

Inventory tracking is the process of recording and monitoring the location, quantity, and activities of stock in a warehouse. It involves generating and updating datasets related to the transportation and administration of materials. This helps ensure accuracy, organized inventory data, compliance, and efficient inventory management

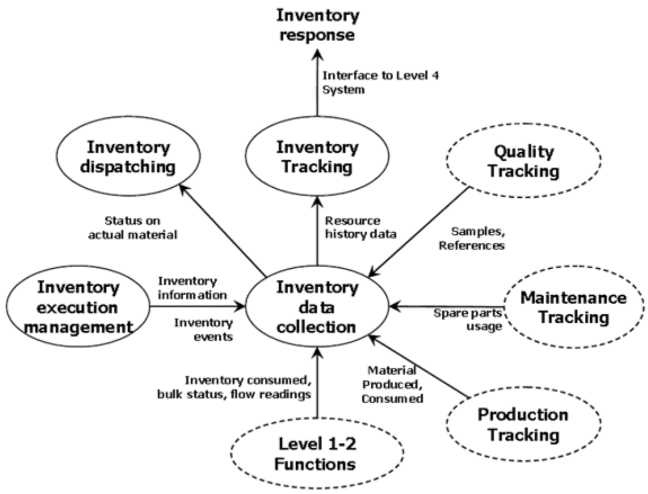

Figure 38. Inventory data collection activity model interfaces. (ANSI/ISA-95.00.03-2005).

Inventory analysis involves evaluating the efficiency and utilization of stock and resources within a manufacturing facility. The analysis includes various aspects of inventory materials, such as material delivery, quality, on-time deliveries, inventory losses, and movements in relation to storage location, equipment, and shifts. Additionally, it involves tracking and analyzing the flow of materials, maintaining a history of inventory resources, and identifying trends.

From the inventory indicators, a set of variables is derived that can be utilized for internal optimization in manufacturing, operations, and management. These variables can also be integrated into the business processes at Level 4. When combined with financial information, they provide relevant cost-related indicators.

The derived indicators are further analyzed and utilized for predicting costs, establishing budgets, and supporting forecasting in areas such as research and development, production planning, logistics planning, sales forecast analysis, and economic analysis. This analysis aids in making informed decisions and optimizing resource allocation throughout the manufacturing operations.

CHAPTER 4 -DIGITAL TWIN

Digital Twin History Overview

The initial concept or basic idea of the "twin" emerged within NASA, notably during the Apollo Program. NASA created and constructed two physically identical spacecraft for this purpose. While one of the spacecaft was launched into space, the other one was retained within NASA facilities to simulate and replicate the conditions experienced by its counterpart in space. (Boschert Stefan and Rosen, 2016)

By building two identical spacecraft, NASA engineers were able to replicate the environment of space on the other spacecraft on Earth. This allowed NASA to test any changes or modifications made to the spacecraft design in a timely manner without having to wait for it to travel through space and back. It was a revolutionary idea at the time and it marked a turning point for NASA in terms of innovation and efficiency. The Digital Twin represents the upcoming wave in simulation technology.(Boschert and Rosen, 2016) as illustrated in the following picture.

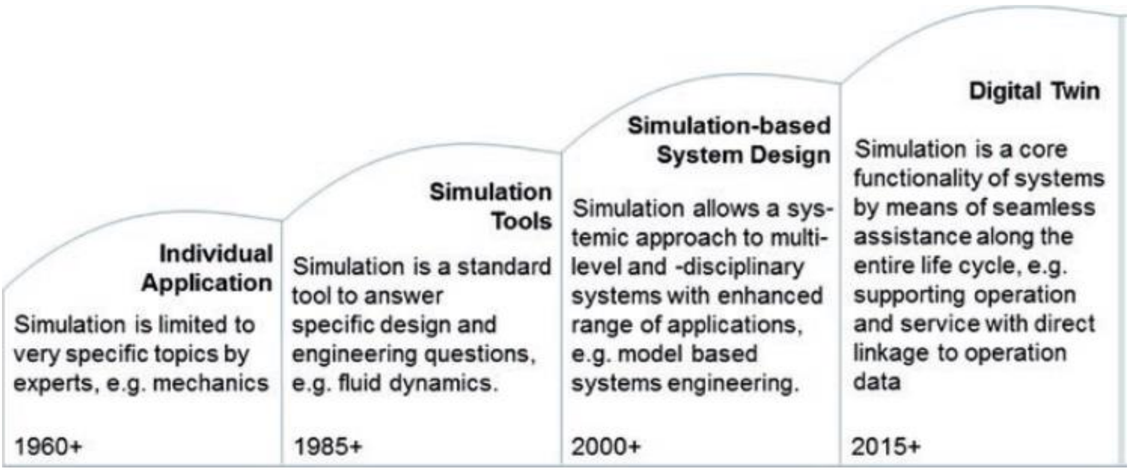

Figure 39. Digital Twin as the next wave in simulation technology. (Boschert Stefan and Rosen, 2016)

In this instance, a digital mirror model could take the place of the spacecraft that is currently in NASA facilities so that high-fidelity simulations can provide more information. By using a digital twin of the spacecraft, NASA engineers could use high-fidelity simulations to test how the craft behaves in different conditions, empowering engineers to make informed decisions regarding its operation and maintenance. By utilizing a digital twin of the spacecraft, NASA engineers can replace the physical counterpart in their facilities and harness high-fidelity simulations to gather more comprehensive information. This digital mirror model allows for thorough testing of the spacecraft's behavior under various conditions.(Boschert and Rosen, 2016)

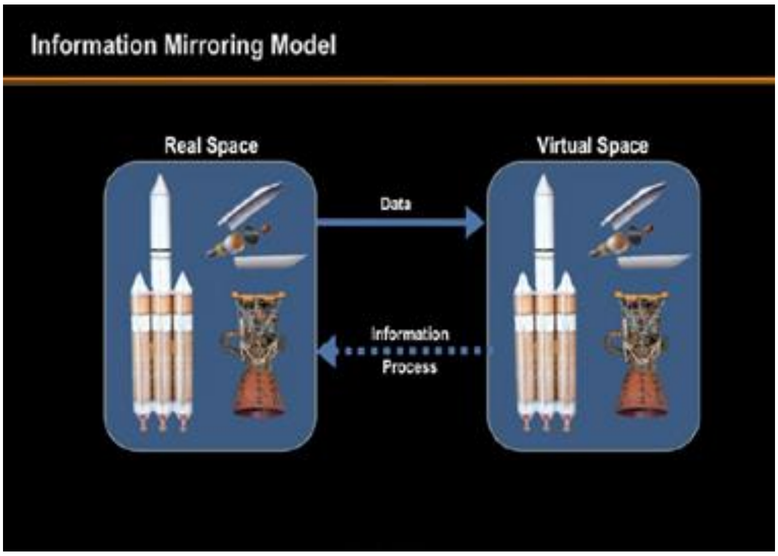

Figure 40. The Digital Twin Concept. (Grieves, 2015)

The concept of the "digital twin" was introduced by Dr. Michael Grieves during his presentation on Product Lifecycle Management (PLM) in 2002 at the University of Michigan. Dr. Grieves referred to it as the "Conceptual Ideal for PLM." The accompanying figure from his original presentation illustrates this Conceptual Ideal. Since then, the concept of the digital twin has continued to evolve and develop.(Grieves, 2016)

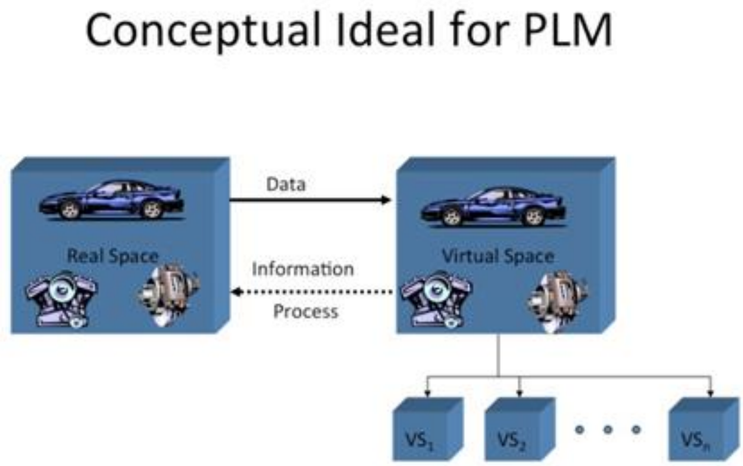

Figure 41 Conceptual Ideal for PLM Dr. Michael Grieves, University of Michigan. (Grieves, 2016)

he Digital Twin, as part of Product Lifecycle Management (PLM), encompasses the structure and elements outlined by Dr. Michael Grieves. These elements include the Real Space, Virtual Space, and the data link pathways connecting the real space to the virtual space, as well as from the virtual space to the subspaces like VS1, VS2, and so on. These components form the foundation of the Digital Twin within the context of PLM.(Grieves, 2016)

The aerospace sector embraced the digital twin with the involvement of NASA and the U.S. Air Force, as noted by Glaessgen and Stargel in 2012. This introduction led to advancements in materials, structures, mechanical systems, and manufacturing processes within the aerospace industry. Leveraging digital twins, the sector achieved efficient and cost-effective monitoring, analysis, and optimization of complex design processes, thus driving further enhancements to the digital twin technology. (Glaessgen and Stargel, 2012)

The growth of the Digital Twin can be depicted in three key stages of evolution, as illustrated in the accompanying figure. These stages include the concept stage, the implementation stage within the aerospace industry, and its subsequent adoption across various other industries.

During the concept stage, the "digital twin" idea emerged as a means of virtually replicating or representing physical assets. (Agnusdei et al., 2021)

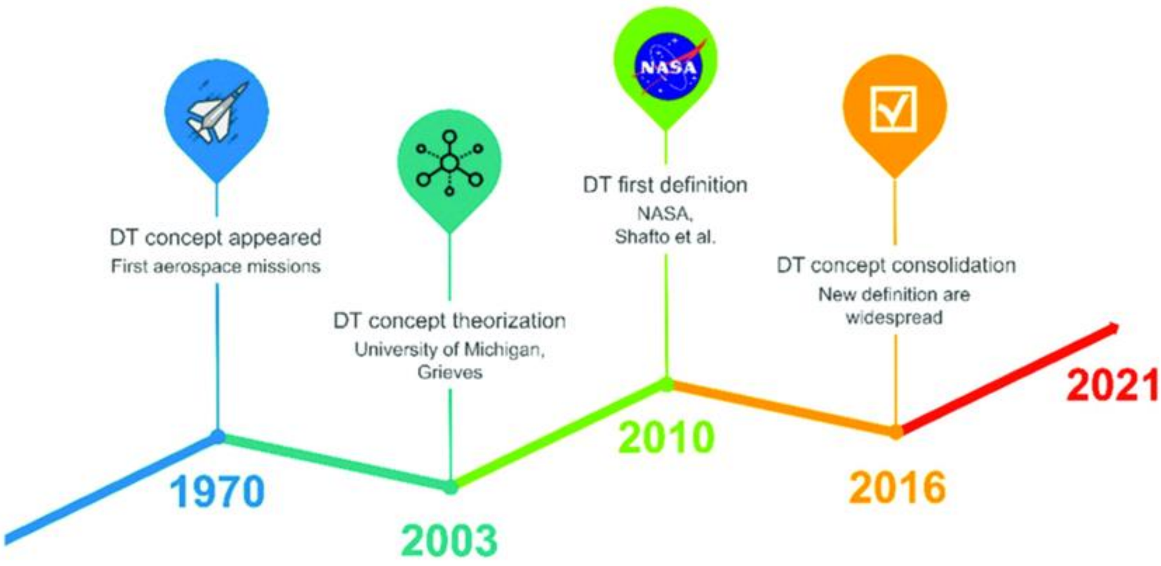

Figure 42 Evolution timeline of the definition of a Digital Twin (DT). (Agnusdei et al., 2021)

The first stage, as proposed by Grieves in 2003 in his paper with the title *"Digital twin: manufacturing excellence through virtual factory replication,"* introduces and defines the three dimensions of the digital twin: a physical entity, a digital entity, and the connection facilitating information flow between the two.(Grieves, 2015)

NASA engineers laid the groundwork for the definition and function of spacecraft digital twins in 2010.In 2011, the U.S. Air Force followed, leveraging the Digital Twin for structural health management applications in aircraft, as highlighted by Tuegel et al. (2011). NASA engineers discovered that digital twins could replicate the physical characteristics of a spacecraft and enable real-time performance tracking, ultimately aiming for enhanced production and operational efficiency. (Tuegel et al., 2011)

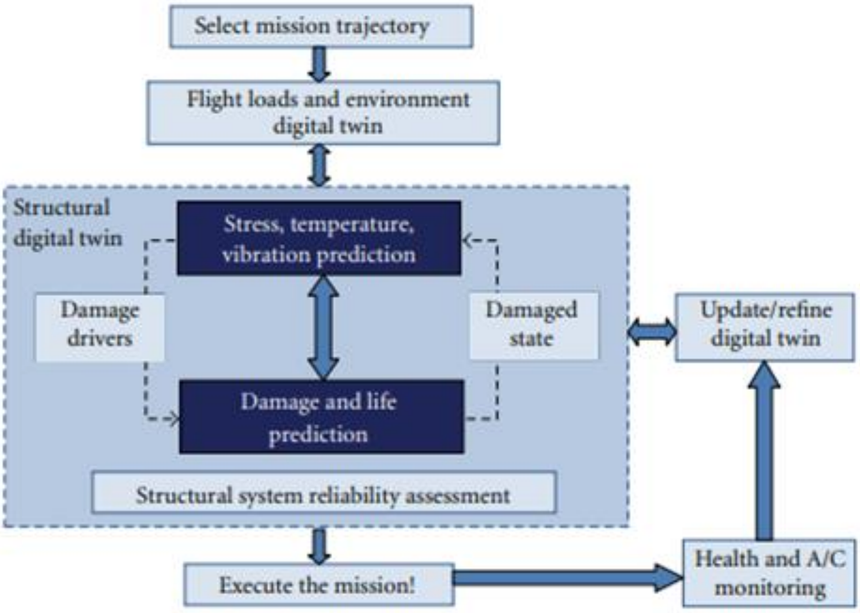

Figure 43 Functional schematic of the Digital Twin life prediction concept. (Tuegel et al., 2011)

Dr. Michael Grieves made the three-dimensional structure of the Digital Twin widely recognized when he published his whitepaper titled "Digital Twin: Manufacturing Excellence through Virtual Factory Replication" in 2014.

Following that, the Digital Twin was introduced and found more applications in industries other than aerospace, such as automotive (Kozłowski and Wiśniewski, 2020), oil and gas (Harshe, 2021), pharmaceuticals, and healthcare.(Simsek, 2022)

In 2017 and 2018, Gartner Symposium/IITxpo 2016 and 2017 in Orlando, Florida, being ranked among the top 10 most promising technological trends in the next decade, the Digital Twin holds significant potential.(Panetta, 2017, 2016)

Academic terms and definitions and the Digital Twin as an Industrial Concept

Various definitions of the Digital Twin have been put forth by the academic community. These definitions provide distinct perspectives on the concept. These definitions highlight the core principles of the Digital Twin, emphasizing its virtual nature, its connection to physical entities or systems, and its utilization for various purposes throughout the lifecycle of the object or system.

Although the core concept of a "digital twin" was initially introduced by Michael Grieves in 2003 within his Product Lifecycle Management (PLM) course, it remained primarily a three-dimensional conceptual structure encompassing a physical object, a virtual counterpart, and their connection. At that time, no concrete explanation or detailed description of the Digital Twin was provided. It wasn't until 2006 that the concept started to develop further and take on a more defined form.

Since then, researchers, scholars, and authors have been proposing their own definitions based on their understanding of the Digital Twin. These definitions may vary in detail across different research fields. However, the underlying concept remains consistent: a comprehensive and dynamic representation of physical assets that integrates real-world data with virtual models.

Despite the variations, the fundamental notion of the Digital Twin remains centered around the comprehensive representation of physical assets, augmented by the integration of real-world data and virtual models. The following table presents a compilation of definitions from various sources, adapted from Fuller et al. (2020a) and Tao et al. (2019c), works, showcasing the diversity of interpretations within different research fields: (Fuller et al., 2020a; Tao et al., 2019c)

Definition and terms of "Digital Twin" - Author/ Date
"An ultrarealistic model of an as-built and maintained aircraft that is explicitly tied to the materials and manufacturing specifications, controls, and processes used to build and maintain a specific airframe" (Eric J. Tuegel, 2012) (B. Gockel et al, 2012)
"Integrating ultrahigh fidelity simulation with an on-board health management system, maintenance history, and historical vehicle and fleet data to mirror the life of a specific flying physical twin to enable significant gains in safety and reliability" (K. Reifsnider et al, 2013)
"A digital replica of real physical installation, which can check the consistency for monitoring data, perform data mining to detect existing and forecast upcoming problems, and use AI knowledge engine to support effective business decisions" (R. Asimov et al, 2018)
"A digital model that flies virtually through the same load history as the actual aircraft wing, integrates various uncertainty sources over the entire life of aircraft wing and heterogeneous information, reduces the uncertainty in model parameters, tracks the time- dependent system states using measurement data, and predicts the evolution of damage states if no data is available" (C. Li et al, 2017)
"A product equivalent digital counterpart that exists along the product lifecycle from conception and design to usage and servicing, knows the product past, current and possible future states, and facilitates the development of product related intelligent services" (J. Rios et al, 2015)
"A digital copy of a product or a production system, going across the design, preproduction, and production phases and Fraunhofer- performing real-time optimization" (R. Soderberg et al, 2017)
"A living model that continually adapts to changes in the environment or operation using real-time sensory data and can forecast the future of the corresponding physical assets for predictive maintenance" (Z Liu et al, 2018)
"A dynamic model in the virtual world that is fully consistent with its corresponding physical entity in the real world and can simulate its physical counterpart's characteristics, behavior, life, and performance in a timely fashion" (C. Zhuang et al, 2018)
"A digital avatar encompassing CPS data and intelligence, representing structure, semantics, and behavior of the associated CPS, and providing services to mesh the virtual and physical worlds" (M. Cianotta et al, 2017)
"A rigorous validation for additive manufacturing process, predicting the most important variables that affect the metallurgical structure and properties of the components, and replacing expensive, time consuming physical experiments with rapid, inexpensive numerical experiments" (G. Knapp et al, 2017)

Table 4 Academic community definitions and terms of the Digital Twin. (Fuller et al., 2020b; Tao et al., 2019c)

When examining the aforementioned explanations, the concept of a Digital Twin can be perceived as a virtual representation that operates in conjunction with a physical object throughout its lifecycle. It generates intelligence and data for the purpose of evaluation, optimization, prediction, and other related activities. The fundamental components of a Digital Twin's three-dimensional framework, as delineated by Michael Grieves in his 2015 whitepaper titled "Digital Twin: Manufacturing Excellence through Virtual Factory Replication," revolve around the fusion of a physical entity, a virtual entity, and the data connection between them. As a result, the origin of the digital twin can be traced back to 2015, when Michael Grieves introduced the concept of a three-dimensional structure, which has since evolved into a vital tool for managing and enhancing physical entities.(Grieves, 2015)

Beyond the confines of academic settings, many businesses have turned their focus to Digital Twin technology due to its wide-ranging benefits and advantages. These include improved dependability and availability through the utilization of monitoring and simulation, resulting in enhanced performance and increased visibility for the business. Moreover, it minimizes the risk of accidents and unplanned downtime by proactively identifying failures, thereby reducing potential disruptions. This proactive approach also leads to reduced maintenance costs by predicting and addressing failures before they occur. Additionally, Digital Twin technology facilitates accelerated product development and guarantees the maintenance of optimal product quality.

Consequently, they combined their businesses and the technology of Digital "digital twin" with their products in order to grasp and achieve more profits and market share by promoting their products and their businesses. With the popularity of Digital Twin technology, it has become an indispensable part of modern industries and businesses.

The following table shows how the companies that made digital twins and used them with their products and business fields saw things.

Company	Industrial Concept
Siemens *Siemens Digital Industries, PLM Automation*	*"A digital twin is a virtual representation of a physical product or process, used to understand and predict the physical counterpart's performance characteristics. Digital twins are used throughout the product lifecycle to simulate, predict, and optimize the product and production system before investing in physical prototypes and assets."* (Siemens Glossary, 2022) (*https://www.plm.automation.siemens.com/global/en/our-story/glossary/digital-twin/24465*)
General Electric Company (GE) GE Digital *Digital Applications*	*"Digital twins are a key piece of the digital transformation puzzle. They create an accurate virtual replica of physical objects, assets, and systems to boost productivity, streamline operations and increase profits. Digital Twin is most commonly defined as a software representation of a physical asset, system or process designed to detect, prevent, predict, and optimize through real time analytics to deliver business value. ."* (GE, 2022) (*https://www.ge.com/digital/applications/digital-twin*)
Dassault Systemes *3DS Blog*	*"A Digital Twin is an executable virtual model of a physical thing or system. That "physical thing" can be anything from a manufactured object, like a car, aircraft, or pharmaceutical drug, or the manufacturing system and process itself, including machines and equipment. Every single product has definable characteristics in the real world, and the Digital Twin combines and portrays the attributes virtually".* (DASSAULT SYSTEMES 3DS Blog, 2022) (*https://blogs.3ds.com/exalead/2019/07/01/what-is-3dexperience-digital-twin-part-1-12-2/)*
ANSYS Company	*"Accelerated Innovation and Cost Reduction with Simulation. Ansys simulation solutions enable materials and chemical process companies to dramatically improve overall equipment effectiveness (OEE), capacity and raw material utilization, resulting in more efficient operations and reduced costs. From equipment and processes to chemical and petrochemical refining to glass, polymer and metals manufacturing, Ansys simulation solutions accelerate innovation for tomorrow's advanced materials systems while helping our customers conserve energy, minimize environmental impacts, meet higher regulatory standards and streamline product development".*(ANSYS, 2022a) (*https://www.ansys.com/industries/materials-chemicals-processing)* *"An analytics-driven, simulation-based digital twin is a connected, virtual replica of an in-service physical asset — in the form of an integrated multidomain system simulation —that mirrors the life and experience of the asset. Hybrid digital twins enable system design and optimization and predictive maintenance, and they optimize industrial asset management".*(ANSYS, 2022b) (*https://www.ansys.com/products/digital-twin/ansys-twin-builder#tab1-1)*

Table 5 Industrial use and concepts of the Digital Twin by Enterprises

(Continued from above table)

Company	Industrial Concept
International Business Machines Corporation (IBM) Company	*"A digital twin is a virtual representation of an object or system that spans its lifecycle, is updated from real-time data, and uses simulation, machine learning and reasoning to help decision-making."*(Armstrong Mae, 202AD) (*https://www.ibm.com/blogs/internet-of-things/iot-cheat-sheet-digital-twin/?lnk=STW_US_STESCH&lnk2=learn_Blogsgen&pexp=DEF&psrc=NONE&mhsrc=ibmsearch_a&mhq=digital%20twin%20definition)*
System Applications and Products (SAP) Company	*"A live digital representation of a connected physical object. Building on the historic definition, a digital twin is a live digital representation (or software model) of a connected physical object. Physical objects such as industrial goods, machines, trains, trucks, wind rotors, appliances, but also factories, farms, or buildings".(Ammrmann, 2017) https://blogs.sap.com/2017/09/09/digital-twins-and-the-internet-of-things-iot/)*
Microsoft Company	*"This pairing of virtual and physical worlds allows monitoring of systems and analysis or simulation of data to head off problems to prevent downtime, optimize overall operations to increase uptime, and even develop new services for the future."* *"To be successful, a digital twin must be intelligent, collaborative, interactive, immersive, and fully contextual within the OEM's enterprise".* (*https://info.microsoft.com/rs/157-GQE-382/images/Microsoft%27s%20Digital%20Twin%20%27How-To%27%20Whitepaper.pdf)*
Infosys Company	*"The Digital Twin collects data from its manufacturing, maintenance, operations, and operating environments and uses this data to create a unique model of each specific asset, system, or process, while focusing on a key behavior (such as life, efficiency, or flexibility). This is the 'model of one.'"*(Colin J. Parris et al., 2016) (*https://www.infosys.com/insights/iot/future-industrial-digital-twin.html)*

Table 5 (cont.) Industrial use and concepts of the Digital Twin by Enterprises

Types and core elements of digital twin.

Physical and Virtual space.

Digital twins bridge the gap between the physical world and the virtual environment, effectively connecting the two realms and reducing their separation. By establishing a link between the physical and virtual spaces, digital twins serve as a powerful tool for analyzing data-rich models in both domains. This integration allows for comprehensive analysis and exploration of the product's behavior and performance, leveraging the benefits of both the physical and virtual environments.(European Commision, 2021; Karakra et al., 2019; Tao et al., 2019c)

The physical space is characterized by its three-dimensional nature and encompasses various objects, including equipment, machinery, buildings. These objects possess tangible properties and attributes like shape, geometric dimensions, size, color, structure, mass, and speed. They can be organized in a structured manner to fulfill specific tasks, taking into account constraints such as time, cost, quality, and other factors. Strategic decisions are essential in this arrangement, considering both the physical properties of the objects and their interactions with each other. (European Commision, 2021; Karakra et al., 2019; Tao et al., 2019c)

The advancement of computer and information technology, along with the emergence, communication technology, the Internet, cloud computing, and the Internet of Things (IoT), has led to the significant expansion of the virtual environment. This virtual realm now plays a crucial role in people's daily activities and lives. It facilitates the conversion of analog data into digital signals, enabling convenient storage, processing, and presentation of information. In the virtual space, each entity is mirrored by a three-dimensional digital model that faithfully replicates the geometry, attributes, and behaviors of its real-world counterpart. (European Commision, 2021; Karakra et al., 2019; Tao et al., 2019c)

The virtual environment has greatly improved our productivity, allowing us to communicate and store information in a more efficient manner and allowing us to perform complex tasks with greater speed and accuracy.

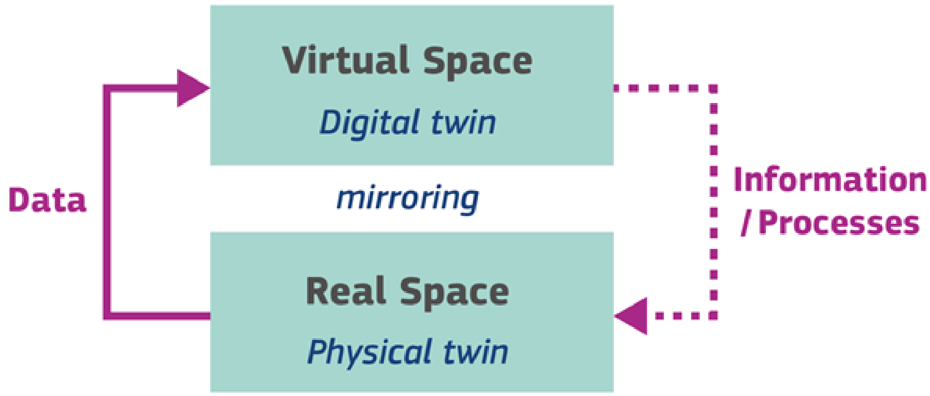

Figure 44 Digital Twin, Physical and Virtual Space. (European Commision, 2021)

The digital twin (DT) encompasses both the physical entity and its corresponding virtual replica. Each entity within the DT possesses a virtual representation that operates, interacts, and evolves in parallel with its real-world counterpart. The digital twin model is constructed and calibrated to accurately replicate the attributes and behaviors of the entity, while striving to adhere to predefined parameters. It establishes bidirectional mappings between the physical and virtual domains, facilitating their integration. This synchronization enables the digital twin to provide real-time updates and notifications regarding changes or issues, allowing for timely intervention. (European Commision, 2021; Karakra et al., 2019; Tao et al., 2019b)

Furthermore, the DT leverages information and data from both the physical entity and its virtual counterpart, enabling comprehensive and precise analysis. By combining and processing data from the physical and virtual spaces, the digital twin can generate more complete insights. It acts as an effective bridge connecting the two environments, facilitating the exchange of information. (European Commision, 2021; Karakra et al., 2019; Tao et al., 2019b)

The digital twin serves as a valuable tool in the digital transformation of various industries, as it enables seamless data exchange and provides an efficient and accurate means of bridging the physical and virtual realms.

The overlapping features and unique characteristics of a virtual prototype and a digital twin.

In the initial stages of the development process, a virtual prototype can serve as a substitute, enabling the identification of defects and the prediction of the final product's behavior. It offers the advantage of easy modification and adaptability when errors or flaws are detected. On the contrary, a digital twin goes beyond virtual prototyping and pre-testing by encompassing additional functionalities.(Tao et al., 2019d, 2019c)

The utilization of a virtual prototype can expedite product development and reduce costs by mitigating the occurrence of expensive errors during manufacturing and shortening the product design cycle. It serves as a valuable foundation for the creation of a digital twin, highlighting both the similarities and differences between the two concepts.(Tao et al., 2019d, 2019c).

By incorporating comprehensive data and contextual information throughout the entire lifecycle of the product, a digital twin offers real-time insights to enhance performance optimization. It also enables predictive maintenance, service optimization, and efficient planning by leveraging the available data.(Tao et al., 2019d, 2019c)

Similarities

- Virtual twins and digital twins are both creating virtual models to replicate counterparts' equivalent physical counterparts. Physical tasks such as product testing, assessment, and validation may be conducted in a virtual environment, reducing both time and financial expenditures.

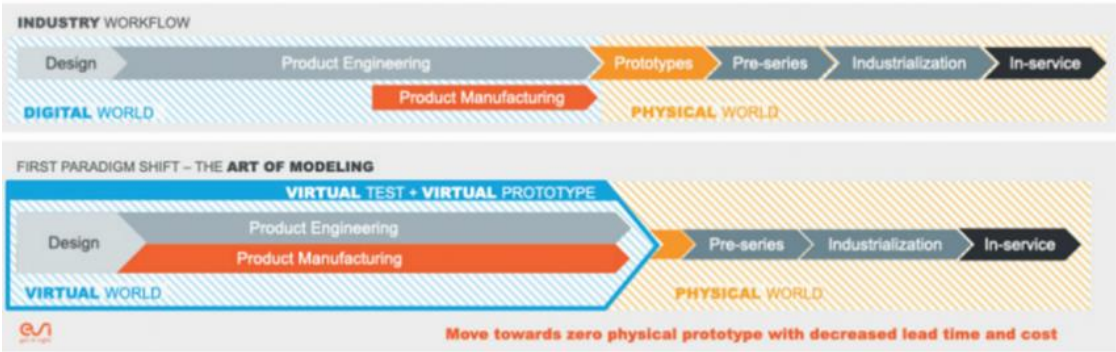

Figure 45 Industry workflow. (ESI Group, 2022)

- Virtual models may provide additional insights to improve and optimize the final output as a product during the design phase.
- Customers may participate in the design process by engaging with the virtual models and sharing their knowledge and suggestions for improving the product.

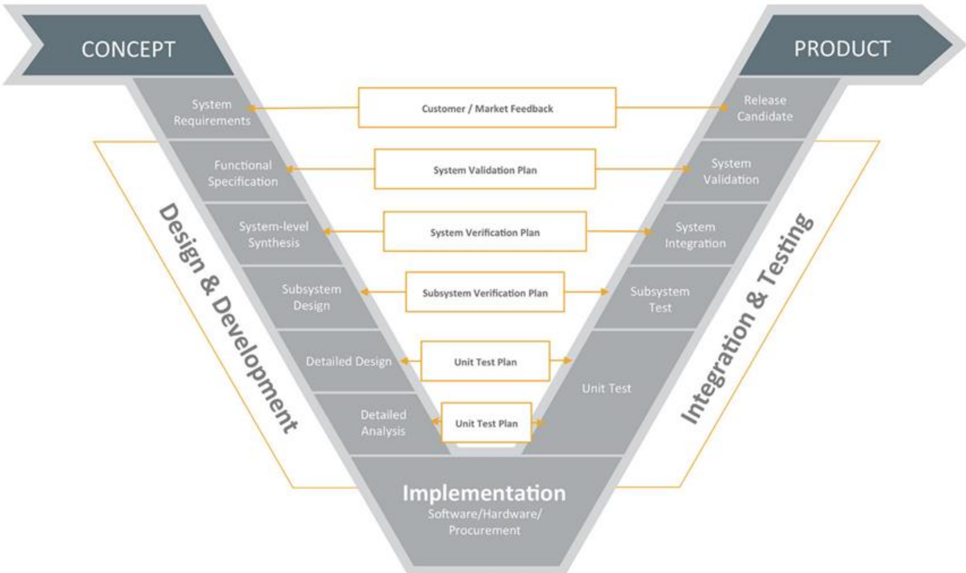

Figure 46 The system design process. The importance of verifying the design against its requirements throughout every stage of the process. Maplesoft (Goossens, 2022)

Differences

The virtual prototype helps to evaluate and validate product designs and development. The DT virtual model follows the physical model from production to disposal during its lifecycle. As DT incorporates online information and real product data from multiple phases (manufacturing, production, supply chain etc,). Digital twin has the ability to account for all possible scenarios within the physical realm. This enables it to conduct comprehensive testing and analysis during the design stage, aiming to minimize potential failures.(ESI Group, 2022; McMahon, 2022). The difference between digital twins and physical prototypes is in their precision and detail, with DT providing a higher level of accuracy.

Virtual prototypes primarily display the idealized version of a product, whereas digital twins have the capability to showcase both the expected and actual product models. In a digital twin, the optimal product model is established during the design phase, and the real product model is continuously updated as actual product data from production, operation, maintenance, and repair phases are incorporated. This offers a distinct advantage, as digital twins can accurately and realistically illustrate any disparities between the envisioned product and its actual implementation.(ESI Group, 2022; McMahon, 2022)

Types of the Digital Twin

A Digital Twin is a virtual replica or image of a physical product, and both entities are interconnected and capable of bi-directional communication. The physical twin can encompass a wide range of objects, from a fully assembled product to a single component, and from an entire production plant to an industrial process, process line, or unit (Grieves, 2016) (Grieves, 2016). The Digital Twin provides a digital representation of the physical product, enabling designers and engineers to make modifications, simulate scenarios, and test potential changes without the need for expensive and time-consuming physical prototyping. This digital representation facilitates faster iteration and validation of design choices, ultimately leading to more efficient and cost-effective product development processes.(Grieves, 2016). According to Grieves (2016), a Digital Twin consists of three essential elements.

- Physical Twin: This refers to the physical part of the system, which could be a product, component, plant, or process.

- Virtual Image or "Twin": The virtual image represents and mirrors the physical twin in a digital form. It is a digital representation that accurately reflects the characteristics and behavior of the physical twin.

- Connection and Integration: The connection and integration between the physical and virtual twins facilitate the flow of data between them. This data flow includes transmission and reception of information, enabling monitoring, imaging, and control of the physical twin.

The data flow between the physical and virtual twins allows for real-time monitoring, analysis, and manipulation of the physical twin's behavior. This interconnectedness empowers designers, engineers, and operators to gain insights, optimize performance, and make informed decisions based on the digital representation and its interaction with the physical counterpart. The concept is illustrated in the following figure demonstrating the relationship and interaction between the physical and virtual elements of the Digital Twin. (Grieves, 2016; Hofbauer et al., 2019)

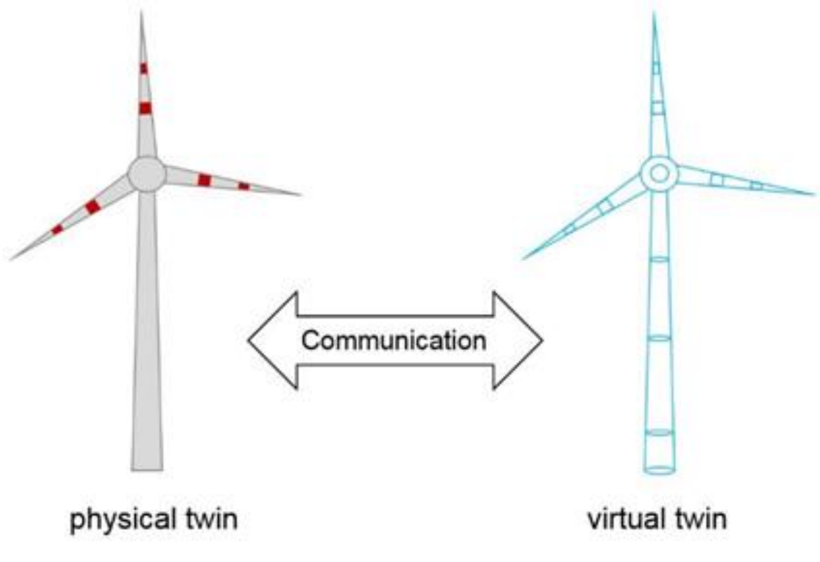

Figure 47 Digital Twin. (Hofbauer et al., 2019)

The concept of a Digital Twin can be further classified into three basic types: Digital Twin Prototype (DTP), Digital Twin Instance (DTI), and Digital Twin Aggregate (DTA). These types are depicted in the provided figure and described as follows. These three types of Digital Twins operate within a framework known as the Digital Twin

Environment. The Digital Twin Environment facilitates the interaction and integration of these different types of Digital Twins by enabling data sharing, feedback exchange, and information retrieval. It provides the infrastructure and platform for seamless communication and collaboration between the Digital Twin Prototype, Digital Twin Instance, and Digital Twin Aggregate. (Grieves, 2016; Hofbauer et al., 2019)

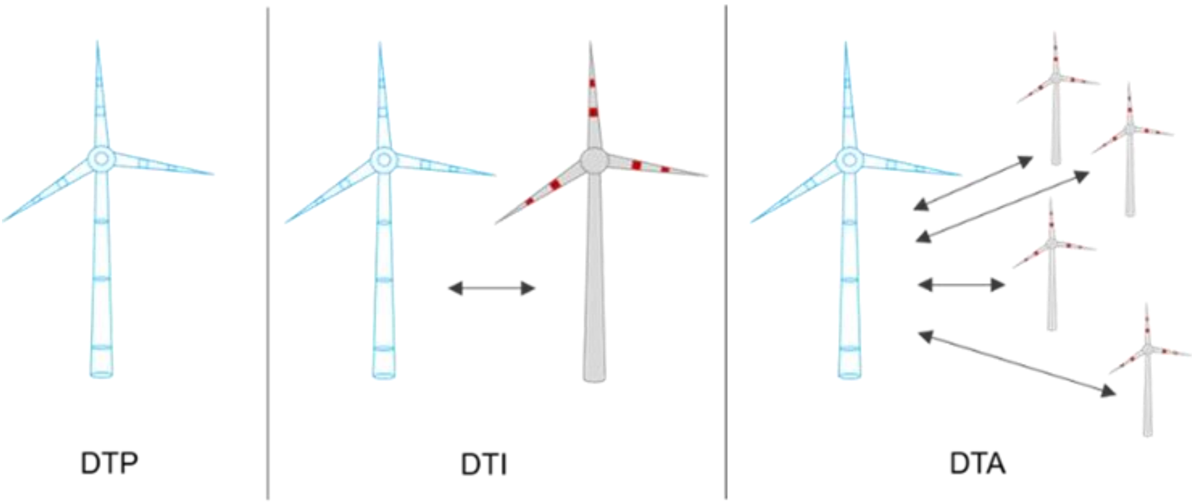

Figure 48 Types of Digital Twin. (Hofbauer et al., 2019)

Digital Twin Prototype (DTP)

DTP means Digital Twin prototype, which represent a virtual / digital image of a product or a component and corresponds only to the initial phase of development of the prototype. So, in this case, and to make it more understandable, the virtual part is developed and designed before the physical part's twin is built. The advantage of the Digital Twin Prototype (DTP) lies in its ability to conduct extensive tests and simulations in the virtual environment during the design phase of a component. These tests and simulations allow for the adaptation and selection of the best possible technical solutions, resulting in a component that is designed with high accuracy and built optimally. During the production stage, the DTP plays a crucial role in achieving the required characteristics of the component. The evaluation of the digital twin prototype becomes particularly valuable for components with sophisticated and complex demands. (Hofbauer et al., 2019)

The virtual prototype contains comprehensive information about the physical attributes, specifications, properties, operational parameters, and more. This information ensures that the production phase can proceed smoothly and error-free. The evaluation of the digital twin prototype is essential in ensuring that the produced component meets the desired physical attributes and specifications. DTP's advantage lies in conducting extensive tests and simulations in the virtual environment, leading to the selection of the best technical solutions and the design of a component with high accuracy. This, in turn, enables a smooth and error-free production phase, ensuring that the component meets the desired specifications and attributes.(Hofbauer et al., 2019)

Digital Twin Instance (DTI)

A Digital Twin Instance represents a specific, individual physical entity or asset in the real world. It is a digital replica of a physical object, capturing real-time data and information from sensors or other sources. This type of Digital Twin enables real-time monitoring, analysis, and optimization of the individual asset's performance and behavior. During the operation phase, the Digital Twin Instance (DTI) collects and processes data related to the usage and working conditions of the physical component. This data is transmitted from the physical part to the digital part through sensors. The DTI also gathers historical and operational data, including statistics on assembly failures, repair records, information on unit replacements and assembly, as well as data on quality control of the physical object. The DTI remains connected to the physical component from day 0 throughout its lifecycle, allowing for continuous monitoring and analysis of its performance and operational parameters. By collecting and analyzing this data, the DTI provides valuable insights into the behavior, health, and condition of the physical component.(Hofbauer et al., 2019)

The data gathered by the DTI can be used for various purposes, such as predictive maintenance, performance optimization, identifying patterns of failure, and improving the overall operational efficiency of the physical component. It enables proactive decision-making and timely interventions to prevent potential issues and ensure the component's optimal performance. DTI plays a crucial role in gathering and processing operational data from the physical component throughout its lifecycle. This data provides valuable insights for maintenance, optimization, and performance improvements, ultimately enhancing the overall operation and lifespan of the physical object.(Hofbauer et al., 2019)

Digital Twin Aggregate (DTA)

A Digital Twin Aggregate represents a collection or aggregation of multiple Digital Twin Instances or other Digital Twins at a higher level of abstraction. It provides a holistic view and analysis of multiple assets or systems, allowing for optimization and coordination across the entire set of interconnected entities. DTA gathers and handles the data of the DTIs to analyze them and present an overall view of the performance of the DTIs. The DTIs can be in one entity, like 10 wind machines in a single wind farm, or they can be in more than one entity, like 5 wind machines in more than one wind farm.(Hofbauer et al., 2019)

Besides the three main types of Digital Twins mentioned earlier, there is another type that emerges in the field of artificial intelligence: the Intelligent Digital Twin (IDT). An Intelligent Digital Twin incorporates advanced artificial intelligence techniques and algorithms to enhance its capabilities and functionalities. It goes beyond the traditional representation and monitoring of a physical object and adds intelligent features to the digital twin system. (Qi and Tao, 2018)

The intelligence digital twins have the advantage of being able to analyze gathered data and predict the product's future behavior based on its current state. This type of digital twin is particularly useful for predictive maintenance, allowing businesses to anticipate and prepare for any potential disruptions or malfunctions in their systems before they occur. By using an intelligent Digital Twin, businesses are able to reduce the number of disruptions they experience in their operations, leading to increased productivity and cost savings. (Qi and Tao, 2018)

Digital Twin Environment (DTE)

According to M. Grieves, the Digital Twin Environment refers to an integrated and multi-domain physics application space that facilitates the operation of Digital Twins for diverse purposes, including predictive and interrogative functions. It serves as a framework where software and hardware components are interconnected and interact with each other. This environment enables the simulation of various scenarios, the execution of commands in complex software systems, and the collection of feedback and recording of results. In essence, the Digital Twin Environment provides the infrastructure and capabilities necessary to effectively deploy and utilize Digital Twins for different applications.(Grieves, 2016, 2015)

A Digital Twin Environment (DTE) can comprise various components, which may come from different providers. These components can be sourced from multiple suppliers and combined to create the DTE. The DTE, being a versioned collection of these components and associated data, represents the virtual counterpart of the physical asset's environment. It serves as the application space where simulation, modeling, and evaluation of Digital Twins (DTs) take place for various purposes. In essence, the DTE provides the infrastructure and platform for operating and leveraging DTs in different applications and scenarios.(Tao et al., 2019c). The DTE serves as an information hub for all components within a Digital Twin, allowing for easy access and exchange of data between multiple sources.

The output generated by a Digital Twin Environment (DTE) can vary based on the specific use case of the customer. It can include event or signal streams, as well as logs that capture relevant information. However, the interpretation of these outputs is often performed by external systems or applications that process the data to derive meaningful insights or results. These external systems may perform analysis, visualization, or other forms of data interpretation to extract valuable information from the outputs of the DTE. This allows the user to make informed decisions and take appropriate actions based on the insights derived from the Digital Twin environment. (Tao et al., 2019c)

Digital Twin Model (three-dimensional–five-dimensional)

A Digital Twin Regardless of the various definitions provided by the academic community or even by companies that developed this type of technology and industry in various application sectors, the key elements of the Digital Twin structure in various sectors include the adoption of digital and physical models, data paths, connections, and services. It involves an evolving three-dimensional (or sometimes five-dimensional) replica of the physical space, capturing its spatial attributes and facilitating simulations and real-time monitoring.

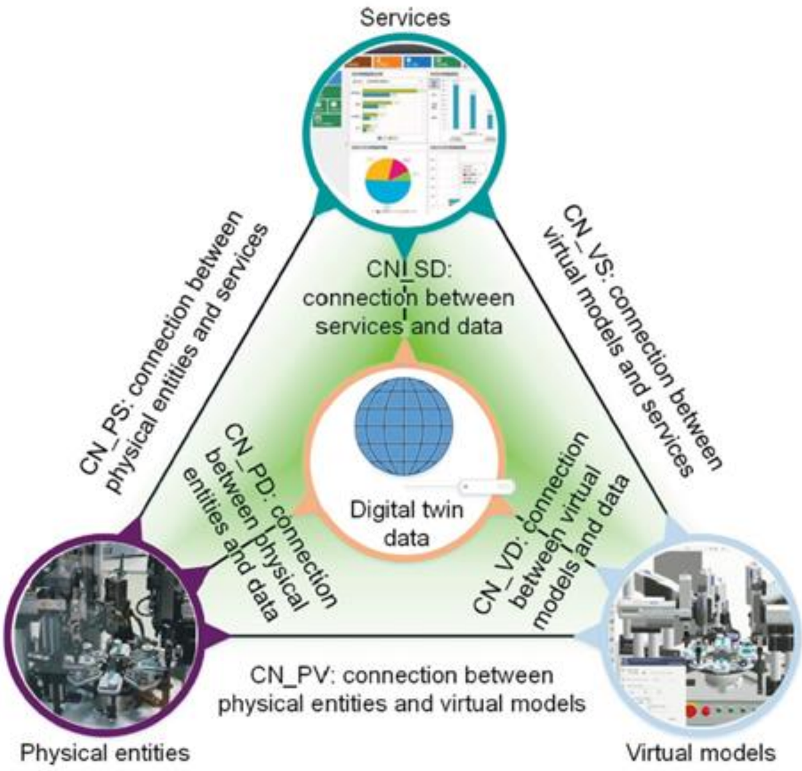

Figure 49 Five Dimension Digital Twin Model. (Qi et al., 2021)

Michael Grieves introduced a three-dimensional Digital Twin model comprising a physical model, a virtual model, and the data connection between them (Figure 1). Building upon Grieves' work, Fei Tao, Meng Zhang, (Tao et al., 2018b) and others expanded the model by incorporating two additional dimensions, resulting in a five-dimensional model (as depicted in the provided figures)

The two new dimensions, namely connections and services, were added to the Digital Twin model. These additional dimensions highlight the dynamic and adaptive nature of Digital Twins, driven by real-time data from the physical model and the interconnectedness between services and their corresponding physical models. This expansion emphasizes the evolving and interconnected nature of Digital Twins in leveraging real-time data and enabling seamless interactions with the physical environment.(Tao et al., 2019e, 2018b)

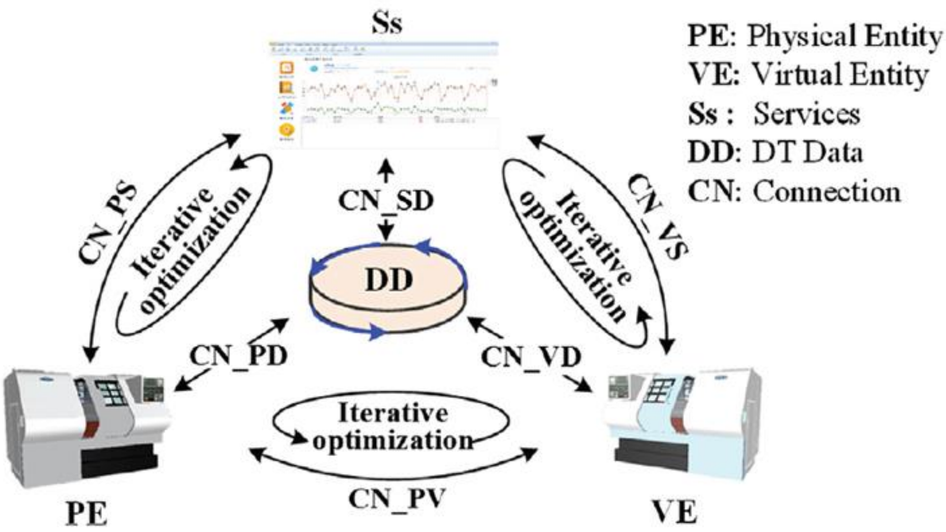

Figure 50 Five Dimension Digital Twin. (Tao et al., 2018b)

The mathematical expressions for the five-dimension digital twin model, (Tao et al., 2019e, 2018b), are the following:

$$M_{DT} = (PE, VE, Ss, DD, CN)$$

where

PE stands for physical entity, which is a real-world object.

VE is the virtual entity equipment, which may contain several digital models.

Ss stands for services for both the Physical Entity (PE) and Virtual Entity (VE).

DD Digital Twin data,

CN Connection among the Physical Entity (PE), Virtual Entity (VE), Services (Ss), and Digital Twin data (DD).

Digital Twin Physical Entity

The primary objective of a Digital Twin is to digitally replicate and simulate the behavior of real-world objects. The foundation of the Digital Twin concept lies in the physical realm, representing the real world. Within the physical domain, a wide range of systems, activities, processes, and entities such as industrial plants or enterprises of different scales can be found. These entities operate according to physical principles and functions within dynamically changing environments, often facing unpredictable conditions.(Tao et al., 2019a, 2018b)

A physical entity typically consists of a variety of different subsystems and sensing elements. The sensors measure and obtain information regarding the status and the operation performance of the subsystems in online and real-time monitoring, such as force, temperature, torque, pressure, vibration, flow, speed, level, capacity, electrical measurements, and so on.(Tao et al., 2018b)

Physical entities can be categorized into three distinct levels based on their structure and purpose: unit level, system of systems (SoS), and system level.(Tao et al., 2019a)

- Unit level: The unit level in DT represents the smallest component within a manufacturing process. It can encompass various entities such as machinery, raw materials, or even the surrounding environment. At the unit level, a DT relies on a model that replicates the physical characteristics, geometry, function, behavior, and operation of the specific unit.(Tao et al., 2019a)

- System level: The system level in DT involves combining multiple DTs at the unit level within a production setting, such as a factory, assembly line, or shop. By linking and integrating DTs at different levels, more comprehensive information can be shared and utilized efficiently. Complex products can also be seen as examples of system-level DTs.(Tao et al., 2019a)

- System of Systems (SoS) level: At the System of Systems (SoS) level, Digital Twin (DT) facilitates collaboration, collaboration among diverse businesses or divisions within organization. It enables coordination and integration across various functional areas. SoS-level DT encompasses multiple system-level DTs that are interconnected and function in synergy. It covers all stages of a product's lifecycle, from design and manufacturing to operation and maintenance. By providing a comprehensive view of the overall system's behavior and performance, SoS-level DT facilitates informed decision-making and optimization of the entire system.(Tao et al., 2019a)

By categorizing physical entities into these levels and implementing DTs at these different levels, it becomes easier to analyze, design, and manage their structure, operations, and interactions within various contexts. Organizations can enhance their understanding, analysis, and management of physical entities, leading to improved efficiency, collaboration, and decision-making across various operational aspects.

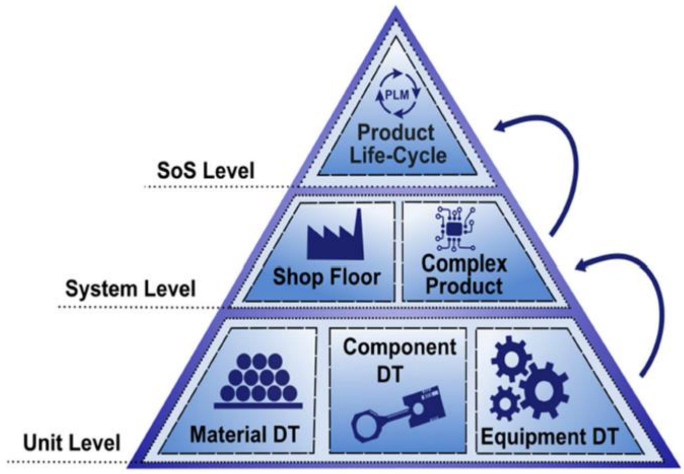

Figure 51. Hierarchical levels of DT in manufacturing. (Tao et al., 2019a)

Digital Twin Virtual Entity

The virtual entity is an exact digital replica of its physical counterpart in every aspect, which can be represented by the following formula:

$$VE = (G_v, P_v, B_v, R_v)$$

of the virtual entity of a digital twin ((Tao et al., 2018b), where

Gv refers to the geometry model. Gv defines the physical entity's geometric characteristics, such as its dimensions, sizes, and assembly relationships.

Pv refers to the physics model. Based on Gv, Pv is provided physical attributes (such as velocity, speed, wearing, pressure, and so on) that may represent and describe the entity's physical processes and phenomena, including distortion, delamination, fracturing, and oxidation. During this stage, the finite element method (FEM) is commonly employed to analyze and calculate the behavior of the entity.

Bv refers to the behavior model. Bv addresses the entity's response mechanisms and behavior patterns, like state transition, and coordination performance deterioration, in response to outside world environment events, factors, control commands, or disruptions from human interferences.

Rv refers to the rule model. Rv is a group of logical guidelines and rules based on associations, constraints, and deductions and is derived from the historical data and information of the physical entity. That group of guidelines and rules provides the virtual entity the ability and power for decision-making assessment, improvement, and optimization, and finally for prediction and forecasting.

In terms of structure, operation, and functionality, the models that include specification regarding geometry, physics, behavior, and rules are all linked and integrated with each other to create a full mapping of the virtual entity for the physical entity. Verification, validation, and accreditation could be used to assess and confirm the Virtual Entity's adequacy and entity.

Even though the Virtual Entity can accurately replicate and create a high-fidelity representation of the Physical object, the level and the degree of precision and accuracy may be customized according to the requirements of the application.

Digital Twin Services

Services play a crucial role in the Digital Twin framework. Ss represents the collection of services associated with both the Physical Entity and the Virtual Entity.

These services are designed to maintain the accuracy and performance of the Virtual Entity while optimizing the operations of the Physical Entity. For the Physical Entity, the services can include state prediction, monitoring, prognostic health management, and optimization services.

On the other hand, services for the Virtual Entity are focused on implementing the models, such as data services, knowledge services, algorithms services, and calibration and verification services.

By leveraging these services, the Digital Twin ensures a seamless integration between the physical and virtual components, enabling accurate representation, monitoring, and optimization of the system throughout its lifecycle.

Ss is made up of components like those that define the functions, input, output, quality, and state of the services.

$$S_s = (Function, Input, Output, Qualtiy, State)$$

Ss may be designed, customized, and configured to satisfy PE and VE requirements and criteria (Tao et al., 2019e, 2018b)

Digital Twin Data

One of the main forces behind Digital Twin is twin data. (Tao et al., 2019b, 2019e), Digital Twin works with data that is heterogeneous, multidimensional, multi-sourced, and multi-temporal. Static attributes and dynamic conditions data are two types of data that are derived from physical items.

Virtual models provide data that indicates the outcome of the simulation.

Services provide data for their invocation and execution, including knowledge from previous data and subject matter experts. Fusion data is generated by combining and synthesizing different data sources. This integrated approach enhances the effectiveness and efficiency of services. (Qi et al., 2021; Tao et al., 2019e)

The following expression containing five components is used to represent digital twin data (DD).

$$DD \ = (D_p, D_v, D_s, D_k, D_f)$$

Where

Dp represents the data gathered from the Physical Entity, specifically related to its working and operation environment.

Dv refers to the data collected from the Virtual Entity, encompassing the model parameters and operational data.

Ds represents the data from the Services (Ss), which defines the combination, integration, execution, and other attributes of the services being utilized.

Dk represents the specialized knowledge that has been derived from the data gathered or acquired from existing systems and databases. It includes expert insights, domain expertise, and other forms of knowledge that contribute to the overall understanding and analysis of the system.

Df represents the merging of the four data sets: Dp (data from the Physical Entity), Dv (data from the Virtual Entity), Ds (data from the Services), and Dk (specialized knowledge). This merging is achieved through data fusion methods and algorithms, which combine and integrate the different data sources to create a comprehensive and unified dataset. Data fusion techniques aim to improve the accuracy, completeness, and reliability of the data by leveraging the strengths of each individual dataset and mitigating their limitations.(Tao et al., 2019e)

Digital Twin Connections

Digital representations, such as Digital Twins, are dynamically connected with their real-world counterparts to enable advanced simulation, operation, and analysis. This connectivity allows for seamless exchange of information and data between physical elements, virtual models, services, and data sources. Through these connections, real-time data can be captured, analyzed, and fed back into the digital representation, enabling continuous monitoring and optimization of the physical system. This integration of the physical and digital realms enhances decision-making, performance analysis, and predictive capabilities, ultimately leading to improved efficiency and outcomes. (Qi et al., 2021; Tao et al., 2018a, 2019e)

For DT, there are 6 connections.

(CN_PV), connection between physical entities and virtual models.

(CN_PD) connection between physical entities and data

(CN_PS) connection between physical entities and services

(CN_VD) connection between virtual models and data

(CN_VS) connection between virtual models and services

(CN_SD) connection between services and data

Connection (CN) is stated as follows (Tao et al., 2019e, 2018a)

CN = [(CN_PV),(CN_PD)(CN_PS) (CN_VD) (CN_VS) (CN_SD)]

Each of them is bidirectional and the delivered data of each connection (denoted as CN_XX) are modeled as follows

CN_XX = (Data Sources, UNIT, Value, Scope, Sampling interval)

The four components - physical entity, virtual entity, services, and digital twin data - can function and collaborate effectively due to the interconnectedness provided by these connections. (Tao et al., 2019e)

Digital Twin and Product Lifecycle Management (PLM)

"*Product Lifecycle Management (PLM) is the business activity of managing, in the most effective way, a company's products all the way across their lifecycles; from the very first idea for a product all the way through until it is retired and disposed of.*"(Stark, 2020) . According to John Stark, Product Lifecycle Management (PLM) refers to the effective management of a company's products throughout their entire lifecycles, from conception to retirement. PLM encompasses the management of product lines and individual components as a cohesive unit. It ensures that the entire spectrum, from small components to the overall product portfolio, is closely supervised. The primary objectives of PLM include maximizing the value of the product portfolio and delivering value to consumers and shareholders. PLM ensures a consistent and streamlined approach to the product lifecycle, covering stages from ideation to design, production, and deployment. (Stark, 2020)

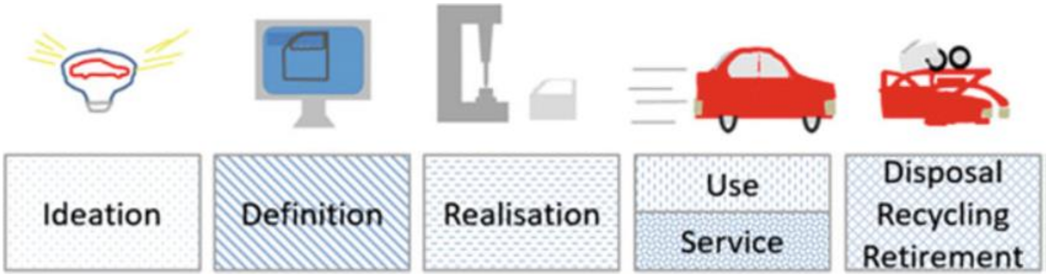

Figure 52 The 5 phases of the product lifecycle. (Stark, 2020)

When it comes to product lifecycle management (PLM), the single most important task is managing the massive amounts of data gathered throughout the course of the product's lifespan. This data can provide invaluable insights, drives products development and production decisions in every stage. Thus, an effective PLM system can help to bring a product from concept to completion in the most efficient way possible, as well as help identify opportunities for improvement along the way.(Stark, 2020)

Data plays a vital role in Product Lifecycle Management (PLM), driving innovation and decision-making. However, the challenge lies in effectively utilizing the vast amount of data collected throughout a product's lifespan. Many organizations aim to extract valuable insights and generate new sources of revenue from their PLM data to maximize its potential. (Easen, 2017; Stark, 2020)

The integration of data throughout a product's lifecycle using the Digital Twin (DT) is a key reason for its popularity in the corporate world. The DT creates a highly detailed digital replica that operates alongside the physical product, capturing real-time data and integrating it seamlessly. This eliminates communication barriers and provides a unified view of the product. The virtual model can simulate, optimize, and validate various aspects of the product, such as manufacturing operations, implementation methods, and environmental factors. By leveraging the DT, businesses can incorporate data into projects, foster innovation, and enhance knowledge exchange. The integration of the virtual replica with the DT leads to improved efficiency, better resource utilization, and waste reduction. (Tao et al., 2019c)

Digital Thread, Digital Twin

The term "Digital thread" was initially defined by Dr. Edward Kraft of the United States Air Force. His definition emphasizes the digital thread as an analytical framework that facilitates the controlled exchange of data, information, and knowledge within an enterprise. The goal is to support decision-making throughout the lifecycle of a system by enabling access, integration, and transformation of disparate data into actionable information. The digital thread is seen as a means to connect and streamline various data sources and enhance decision-making processes. (Kraft, 2015)

In the context of military projects, the digital thread plays a crucial role in leveraging digital technologies to improve various aspects of aircraft manufacture, operation, and maintenance. It involves the integration and utilization of high-fidelity digital models, sensor data, and knowledge throughout the lifecycle of the aircraft. By utilizing the digital thread, data from various sources within the digital thread, such as models, sensor data, and knowledge, can be gathered, assessed, analyzed, and updated as needed. This enables informed decision-making, enhanced assessment capabilities, and improved maintenance practices.(Kraft, 2016)

The digital thread extends beyond aerospace and is now utilized in various industries, including civil sectors. It enables connected data flow and an integrated view of product data throughout its lifecycle, breaking down silos between functional perspectives. This approach improves communication, efficiency, and decision-making, leading to enhanced product design, manufacturing, and service. (Leiva, 2016).

The digital thread serves as a unified framework that ensures the right information is available at the right time and place. "the right information to the right place at the right time". (Leiva, 2016) This capability has led many large organizations to prioritize the digital thread and pursue complete automation and digitization of their supply chain, production processes, and operational functions. By doing so, they aim to stay competitive in an increasingly demanding business environment. (Leiva, 2016)

Because of this, a lot of big organizations are emphasizing the digital thread and aiming to totally automate and digitize their supply chain, production process, and other operational functions in order to meet the demands of the growing competition.

When used in conjunction with the digital twin, the digital thread collects and integrates data and information throughout the entire life cycle of the product. This enables high-quality mirroring and simulation of the physical asset. By adopting this approach, organizations can experience benefits such as increased accuracy, improved product design, and faster time-to-market. In many cases, product lifecycle activities are fragmented due to the use of different software and, information tools, by various teams within the organization. However, by connecting and integrating these processes and functions, organizations can achieve higher automation, and efficiency, while also reducing errors and faults. By embracing the digital thread and digital twin approach, organizations can leverage the benefits of connectivity, integration, and automation to enhance their product development and manufacturing processes, ultimately driving efficiency, accuracy, and competitiveness. A digital thread connects and integrates data throughout the product lifecycle, ensuring data accuracy, traceability, and compliance while maintaining a consistent standard. It provides a unified view of the product's data from design to end-of-life, enhancing efficiency and decision-making. (Qi et al., 2018; Qi and Tao, 2018; Shi - Wan Lin, 2017)

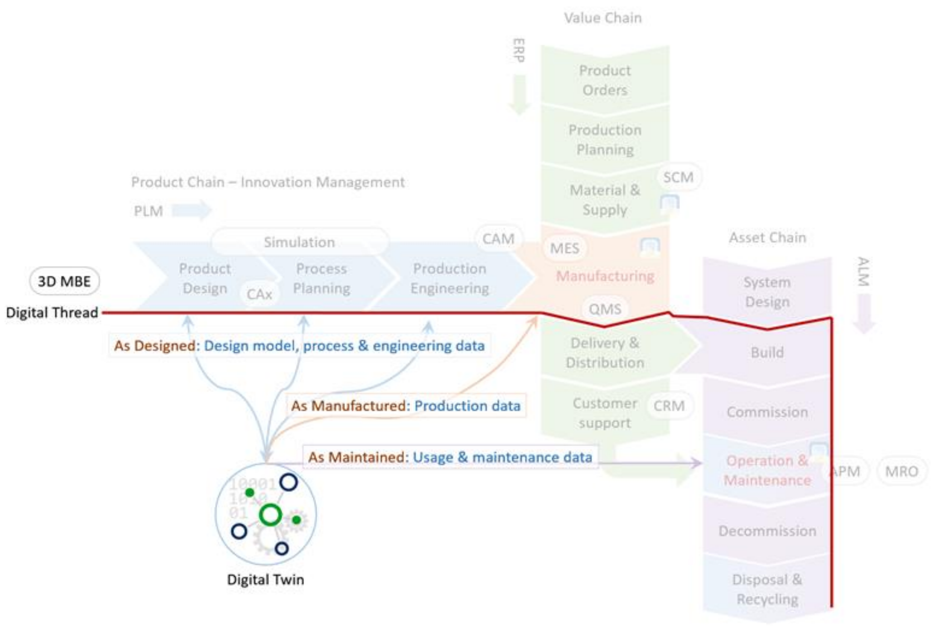

Figure 53 Digital Thread and Digital Twin. ARC Advisory Group, 2017 (Shi - Wan Lin, 2017)

In the above figure, the digital thread is shown to maintain an interactive and integrated connection with the digital twin throughout the lifespan of the product. This integration enables the digital thread to continuously drive the operation and functioning of the digital twin by providing real-time data, feedback, and updates. The digital thread serves as a communication framework that facilitates the flow of information and ensures the seamless integration of data across various stages of the product lifecycle. This interconnectedness between the digital thread and the digital twin allows for efficient monitoring, analysis, and optimization of the product's performance, leading to improved operation and functionality. The digital thread serves as a conduit for information flow, facilitating seamless data exchange and supporting decision-making processes across different domains within the product's ecosystem. .(Buntz, 2017; Shi - Wan Lin, 2017)

The different sources of data are linked and integrated within the digital thread, allowing for the seamless flow of information to and from the digital twin. This enables the digital twin to analyze, optimize, and predict the behavior of the physical asset based on the received inputs. The outputs generated by the digital twin, such as simulated data and insights, are then fed back into the digital thread. In response to these inputs, the DT analyzes, optimizes, and predicts the physical asset and sends as outputs a quantity of simulated data, which has been subsequently supplied back to the thread in response. The aim of the digital thread is to streamline production processes by leveraging digital technologies. This streamlining leads to increased speed, efficiency, and reduced human errors. By digitizing and automating various aspects of production, organizations can achieve higher productivity, better quality control, and more effective resource utilization. The digital thread acts as the backbone that enables the seamless integration and synchronization of data, fostering a more streamlined and optimized production environment.(Shi - Wan Lin, 2017)

With the digital twin, all the important information about a product, including its design specifications, manufacturing data, and instructions for use and maintenance, can be easily gathered. This information serves as the foundation for creating product models that accurately represent the product's current condition and historical data throughout its entire lifecycle. These models, backed by comprehensive product data, provide a dynamic and up-to-date depiction of the product, enabling better understanding, analysis, and decision-making. (Shi - Wan Lin, 2017)

Using product models, designers can access and share relevant product data during the lifecycle of a product and thereby minimize errors, increase efficiency, reduce waste, and realize significant cost savings. Having all the needed components, it is able to connect physical objects and their virtual replicas into a digital thread. Within it, the following repetitive procedures are taking place.(Bowers, 2017)

Digital twin is a virtual replica of a physical object that can be actively utilized working and updated throughout its lifecycle. It specifies the structure and engineering systems, parts and components and the attributes with the behavior of the material used, including data for the operation ensuring the optimal functioning of the physical object .

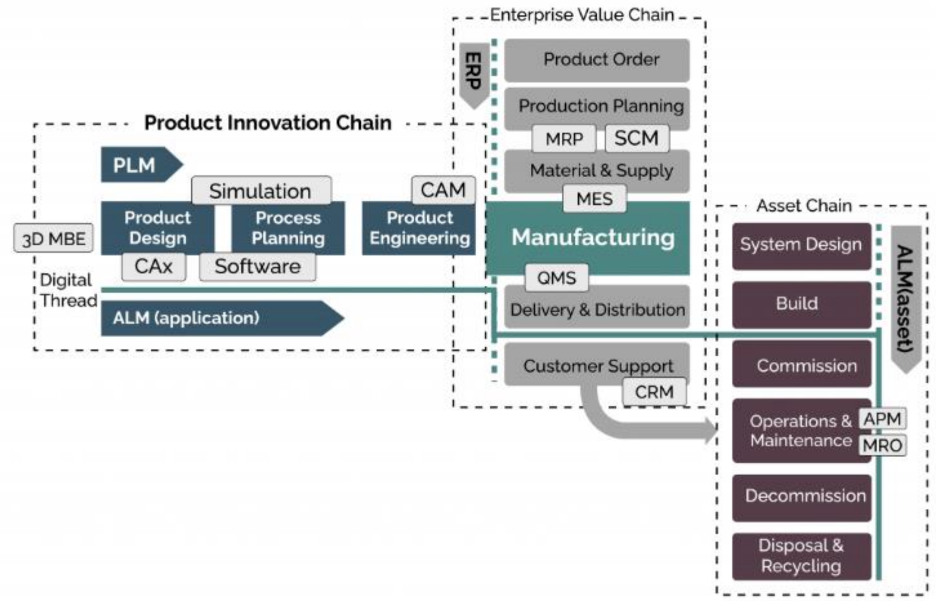

Figure 54 Digital Thread and Digital Twin. (Radiant, 2023)

The digital thread facilitates seamless data flow and provides a holistic view of an asset's lifecycle, enabling collaboration, informed decision-making, and proactive issue resolution. It improves efficiency and reduces costs by identifying and addressing problems in real-time. (Radiant, 2023)

A clearer view of the information flow is depicted in the following figure:

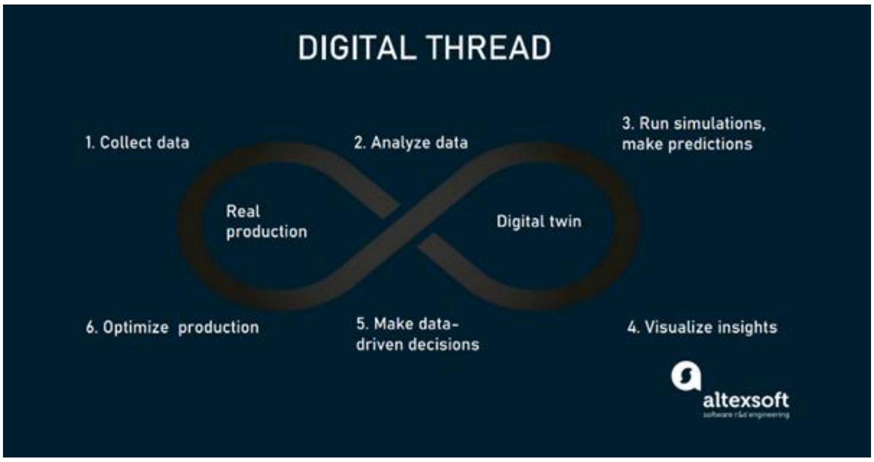

Figure 55 Steps within a digital thread. (Altexsoft, 2021)

Data from a physical object and its environment is collected and transmitted to a centralized repository. The collected data is processed and analyzed to extract meaningful insights and information uses as an input to the digital twin. The digital twin utilizes the input data to perform simulations and predictions based on the virtual model. The results and insights from the analytics are visualized in a user-friendly manner for stakeholders to understand and interpret. Stakeholders use the insights provided by the digital twin to make informed and data-driven decisions. Based on the decisions made, adjustments can be made to the physical object's parameters, processes, or maintenance schedules. The cycle of data collection, analysis, visualization, and decision-making is repeated based on the new data. The cycle of data collection, analytics, and visualization, decisions making based on the insights, is continuous.(Altexsoft, 2021)

And from the perspective of technological trends, that powering digital twin, the functionality, complexity, integrations, and technologies of each type vary in some way. As technology systems are integrated, the digital twin evolves to become more comprehensive and intelligent. This development creates a digital thread that brings both challenges and opportunities for stakeholders. Emerging technologies enable valuable digital twin outcomes by integrating the physical and digital worlds. (Altexsoft, 2021; Shi - Wan Lin, 2017)

The digital twin offers enterprises the ability to model and simulate physical assets in the virtual realm, allowing for better insights and decision making. It also presents opportunities for technology vendors to offer specialized solutions for specific industries and use cases. However, the growing complexity of digital twins can also lead to challenges in data management, security, and interoperability. Therefore, it is crucial for organizations to select the right technologies to ensure successful implementation and utilization of digital twin systems.

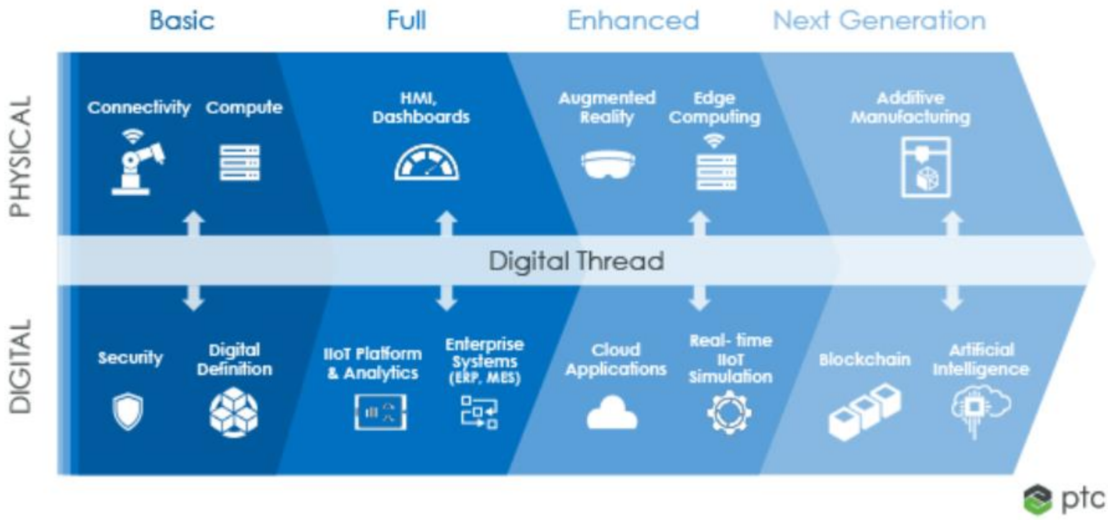

Figure 56 Technologies powering Digital Twin. PTC,.(Immerman, 2018)

Basic Stage: In terms of value creation, certain fundamental technologies can meet the minimum requirements for a digital twin and outperform lighter digital replicas and shadow categorizations. In order to support processing, data storage, and data generation, the physical asset requires access to servers located either on-premises, in the cloud, or at the edge. These server resources provide the necessary computing power and infrastructure for handling the data requirements of the asset. To send this data, you need reliable connectivity. Any type of internet-connected device or connectivity requires careful security measures to protect the server, network, data, and device's integrity. The systems for keeping track of the asset's history must be defined in a digital format that can be accessed in some way. Having asset histories in digital format ensures that information is readily available and can be easily retrieved. Furthermore, digital systems allow for accuracy, reliability, and speed of information, improving decision-making processes. (Immerman, 2018)

Full Stage: An Industrial Internet of Things (IIoT) platform becomes essential for connecting, interpreting, and interacting with various physical systems, enabling real-time data transfer from sensors to the digital twin. This connectivity allows the digital twin to fulfill its purpose effectively as it evolves. Additionally, interconnections between enterprise business systems, such as ERP (Enterprise Resource Planning) at the organizational level and MES (Manufacturing Execution System) at the factory shop floor level, provide crucial contextual data sets for both levels. (Immerman, 2018) Authorized personnel have access to this digital twin data via HMIs, PCs, etc. This integration makes it easy for the two levels to talk to each other and make their operations run as smoothly as possible. This opens the door to more productivity and efficiency. However, ensuring smooth data flow and preventing information silos remains a key challenge for organizations implementing these systems. (Immerman D, 2019)

Enhanced Stage: Emerging technologies in the enhanced stage, such as edge computing and analytics, will play a crucial role in transmitting twin model data files and optimizing assets efficiently. (Immerman, 2018)

Edge computing and analytics make it possible for an asset that is physically connected to the network to process data locally and only send data that needs to leave the device. (Immerman, 2018)

With the availability of augmented reality headsets, front-line workers can access twin data and view digital representations alongside physical assets for more immersive interactions. (Immerman, 2018)

The IIoT platform is used as a way to get more information into the digital twin. This is done through cloud-based apps and IIoT simulation models, which predict what machines will do in real time basis created on data from the past and from the real world. When IIoT is added to the digital twin, it makes it easier to track performance and plan maintenance. By looking at data from sensors and machines, the platform can find problems before they get too big.

Additionally, the platform can facilitate greater collaboration between teams by providing real-time data and insights, enhancing the decision-making process, and fostering innovation.(Immerman, 2019)

Next-Generation Stage: Because of the digital twin, business models for future industrial product models, such as additive manufacturing, will change in a big way.

Product designers can leverage the access to real-world operational performance through a feedback loop to modify virtual product models and 3D print subsequent iterations or replacement spare parts. This integration of the feedback loop enables continuous improvement and optimization of the product design process. (Immerman, 2019, 2018)

By harnessing the data from various integrated twin sources, AI-related technologies such as machine learning and deep learning algorithms can extract valuable operational insights and enhance the efficiency of assets. These technologies analyze the data to identify patterns, trends, and optimization opportunities, leading to improved asset performance. (Immerman, 2019, 2018)

Blockchain technology plays a crucial role in ensuring data validation and enhancing security and transparency throughout the supply chain for a product's lifecycle. With its decentralized digital ledger, blockchain validates data feeds from different stakeholders, facilitating trust and enabling the generation of fresh insights for the digital twin. By putting these two technologies together, businesses can learn more about how their assets work and where they are in the supply chain. This can help optimize operations, reduce costs, and improve overall customer satisfaction. (Immerman, 2019, 2018)

Digital Twin serves as a means to depict the interconnectedness and mapping between the real and virtual worlds. It can be categorized into two distinct types: entity DT and scenario DT. Entity DT utilizes 3D geometric models to integrate data from various sources, including information about the entity's location, movement, state, and behavior. It provides a comprehensive representation of the physical object or system in the virtual realm.(Qi et al., 2021) Scenario DT, on the other hand, employs static and dynamic data from the real world to create an accurate virtual representation of specific scenarios. It allows for the simulation and analysis of real-world situations in a virtual environment.(Qi et al., 2021)

DT applications cover a wide range of functionalities, such as functional modeling, concept verification, behavior simulation, performance optimization, status monitoring, diagnosis, and prediction. Integration between entity and scenario DT is crucial for fully leveraging the capabilities of DT and achieving its maximum potential. (Qi et al., 2021)

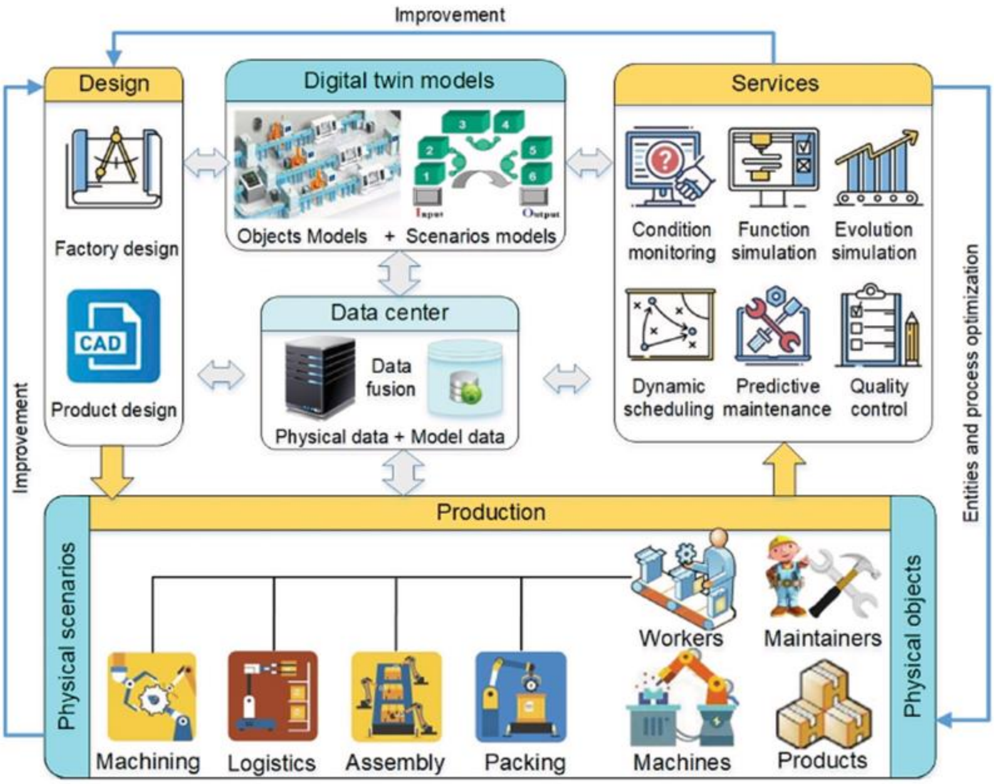

Figure 57. Composition and application of digital twin. (Qi et al., 2021)

First and foremost, DT facilitates the digitalization, visualization, and materialization of complex systems with numerous components and implicit couplings during the design process. Also, DT makes it possible to compare, test, and evaluate good design plans without having to build expensive physical prototypes by simulating the design, you can find out if it is good enough to be made and if it works the way you want it to. In this manner, the design and production teams can work together to address any design or quality issues with the product.

Through simulating, verifying, and confirming process planning and production scheduling, Digital Twin (DT) enables the optimal (re)configuration of on-site resources, equipment, work-in-progress (WIP), and workers from a production management perspective. It allows for effective control and execution by leveraging operational forecasting, optimizing control strategies, and aligning processes based on real-time data from the physical world. DT empowers production management to make informed decisions, improve operational efficiency, and maintain process alignment for better overall performance.(Qi et al., 2021; Zhang et al., 2020)

By utilizing DT, real-time monitoring and adjustment of production processes become possible, leading to increased agility and responsiveness in handling unexpected events.

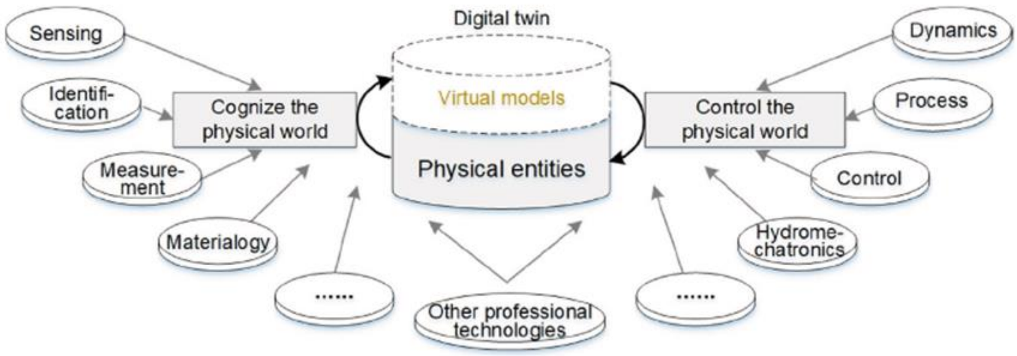

Figure 58. Enabling technologies for cognizing and controlling physical world. (Qi et al., 2021)

To create realistic models, it is essential to have a strong understanding of how the real-world functions and to effectively interpret data. The measurement of parameters such as size, shape, structure, tolerance, surface roughness, density, hardness, and others are crucial in the initial stages of building an accurate representation of the physical world.(Qi et al., 2021)

Real-time data, encompassing variables like temperature, humidity, torque, pressure, displacement, speed, acceleration, vibration, current, voltage, and more, is necessary for achieving synchronization between a virtual model and its physical counterpart.(Qi et al., 2021)

High-end digital twins continuously gather real-time data from sensors and systems to provide an accurate portrayal of the current state of physical entities. Models used for structural analysis, evolution, and fault prediction can significantly vary across different sectors.(Qi et al., 2021)

Digital Twin, Digital Shadow

Digital shadow is a data footprint (operation data, condition data, process data) that remains coupled to the corresponding entity (digital or physical) throughout its lifespan and circulates all data information in order to depict characteristics such as historical data, current status data, and forecasted status data via an intelligent linkage path (Stark et al., 2017)

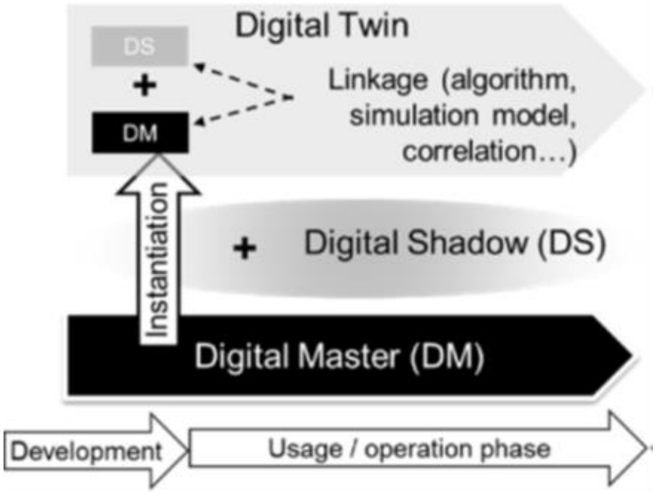

Figure 59 Digital twin, digital shadow and digital master. (Stark et al., 2017)

As per Dalmolen S. et al, "Digital Shadow" refers to a digital information on an object that is constantly gathered, enhanced, and protected on its behalf and accessible from a single access point. An object may have a digital existence via its digital shadow, which also allows for cooperation between them. The "digital shadow" is a depiction of an actual item in the real world, it depicts its unique characteristics, background, present situation, and forecasted future. Digital shadow refer to a virtual agent or representation that collects, stores, updates, and shares information on behalf of the entity it represents. (Dalmolen et al., 2012).

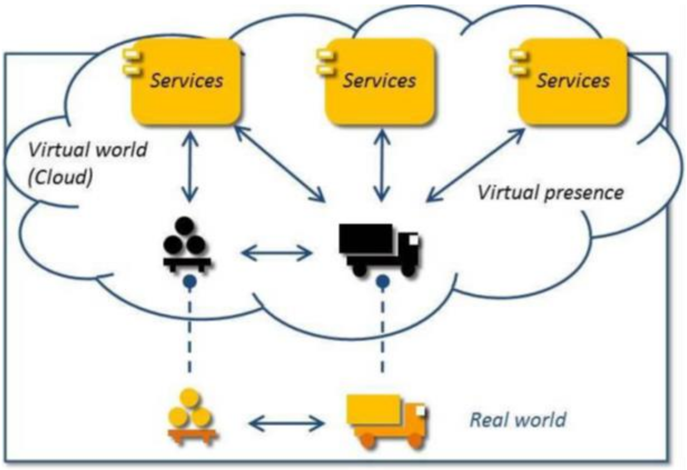

Figure 60. Cargo's Digital Shadow. (Dalmolen et al., 2012)

The above figure provides an illustration of a digital shadow and how it relates to the actual physical world. An item or entity in the virtual world is represented by its digital equivalent of a shadow, which exists in the physical world. In addition to keeping an eye on its counterpart in the actual world (the physical world), it is also capable of performing the functions of a human personal assistant in a virtual capacity in order to act in the entity's best interest. A digital shadow is an agent that lives in cyberspace rather than on the actual physical thing being shadowed. The digital shadow can serve as a source of information and provide insights or assistance in decision-making processes.

The main objective of the digital shadow is to support decision-making processes by maximizing the utilization and efficiency of physical resources (Dalmolen et al., 2012). It plays a crucial role in ensuring digital security and minimizing potential digital risks. To accomplish these objectives, the digital shadow requires comprehensive and detailed information about the physical counterpart it represents. This information enables effective analysis, monitoring, and decision-making based on the real-time status and behavior of the physical entity (Dalmolen et al., 2012).

According to Fuller et al. (2020), a Digital Shadow is a digital representation of a physical object in the real world that facilitates one-way flow of data and information. It captures and reflects the state of the physical item, and any changes in the physical item result in corresponding updates in the digital representation. However, the Digital Shadow does not have the capability to influence or modify the state of the physical item. Its purpose is to provide a synchronized and updated digital reflection of the physical object's status and characteristics.(Fuller et al., 2020b)

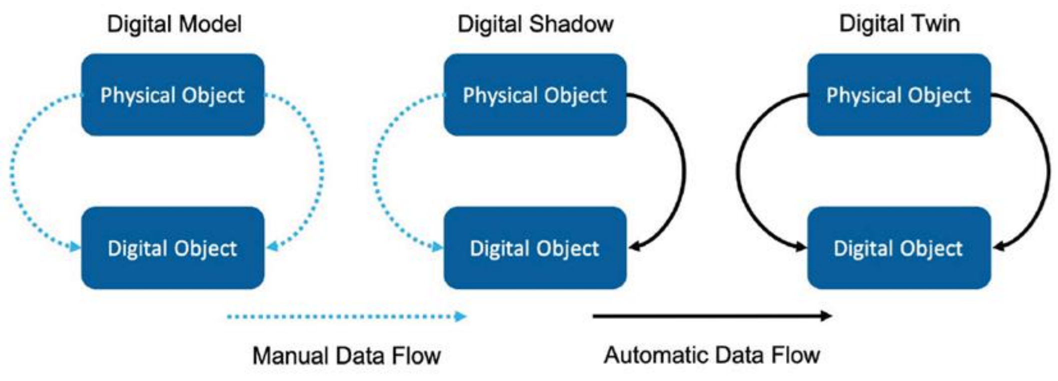

Figure 61 Digital Model Shadow and Twin. (Fuller et al., 2020b)

To describe a digital model, it implies that there is no automatic sharing of data between the physical model and the digital model. The two models do not interact or exchange information in a synchronized manner. The digital model serves as a separate representation of the physical item without any real-time connection or bidirectional data flow between them. Changes or modifications made to the physical item do not affect the digital model, and vice versa. The digital model remains independent and does not automatically reflect updates from the physical item. A digital model is a digital replica of a physical item, either existing or projected. In this type of model, there is no automatic data exchange between the physical system and the digital model. Once the digital model is created, any changes made to the physical item do not affect the digital model, and vice versa. This unidirectional flow of information distinguishes a digital model from other forms of digital representations. (Fuller et al., 2020b)

On the other hand, if information and data flow in both directions between a physical entity and a digital entity, and both the physical and virtual objects are fully integrated, it is referred to as bidirectional flow. In this case, if changes made to the physical form are automatically updated in the corresponding digital representation, and vice versa, the term "Digital Twin" is used to describe this relationship between the two versions.(Fuller et al., 2020b)

The concept of the digital shadow shares similarities with that of the digital twin, as both involve virtual representations of physical objects that transmit and receive information. However, there are distinct differences between the two.

The digital twin is a precise replica of the physical counterpart, reflecting its properties, behavior, and interactions. It is created based on real-time data and provides a means to monitor and analyze the physical asset's performance, make predictions, and optimize its operation. On the other hand, the digital shadow is a dynamic relationship between the physical object and its data counterpart. It encompasses the continuous flow of information and data associated with the physical object throughout its existence. The digital shadow evolves as new data is collected, analyzed, and integrated, allowing for improved understanding and insights into the object's behavior, usage, and conditions. While the digital twin focuses on creating a virtual replica of the physical asset, the digital shadow emphasizes the ongoing relationship and integration of data to enhance knowledge and decision-making related to the physical object.(Tao et al., 2019c, 2019b, 2019a)

The digital twin is a virtual replica of a physical object that captures and exchanges information throughout its entire lifespan. In contrast, the digital shadow represents the evolving relationship between a physical object and its associated data.(Tao et al., 2019c, 2019b, 2019a) Here are the key differences between the two:

- Representation: The digital twin provides a comprehensive and intuitive mirror representation of the entity.

- Testing and Validation: The digital twin enables testing and validation of physical activities and processes before they are implemented, reducing the risk of failure.

- Real-time Communication: The digital twin maintains constant communication and synchronization with the physical entity to compare actual and simulated behavior in real time for assessment, optimization, and prediction.

- Data Integration: The digital twin combines data from the physical world, virtual models, and other sources, allowing for synthesis, statistics, association, grouping, evolution, prediction, and refinement. More data leads to more accurate and complete information in the digital twin.

This brings several benefits to businesses and industries, including enhancing product and service reliability, reducing costs associated with testing physical processes and activities, optimize operations by using real-time analytics, minimize risk through predictive analysis, and enable faster decision (Wizata Team, 2022).

Digital Twin Benefits, Advantages, and Disadvantages

Digital twin application serves as the tool used to make a map of all the parts of a product's life cycle. This includes how to handle and use both virtual and physical data, as well as how information flows between a physical and its virtual counterpart and how they interact with each other. Since there are fewer possible downsides than upsides for the end user, they will be listed briefly and not explained in detail.

- The network connectivity specifications play a crucial role in determining the usability and effectiveness of the digital twin.
- The security of the data and network from outsiders and cyberattacks is always an important and possible problem that needs to be thought about carefully and designed with the best cybersecurity protection.

Digital twin has many benefits because it improves and expands the performance of processes and their final products. This shows that the efficiency of the production process is being optimized and improved at every step.

A digital twin is a great way to test new technologies virtually so that they behave the same way and any potential problems can be found and fixed.

Also, they help keep track of activities in real time and make sure that actions and states happen as often as possible. It is possible to measure how well a process or product is doing in real time with as little cost and productivity loss as possible. It is a great tool to increase the speed and effectiveness of production and delivery, while simultaneously minimizing the risks involved.(Arnautova, n.d.; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, n.d.)

Visibility and Real-Time Monitoring

The Digital Twin provides high-fidelity models, which are constantly updated from feeding in real-time from the integrated data through sensors in order to maintain consistency with the physical entity. Enables and allows the operators or users for monitoring and controlling processes, production lines, systems, and subsystems in a more accurate and direct manner. It is hard for the people who run a complex and large physical system like a refinery or industrial plant to see it in real time and in detail. A digital twin can be accessed remotely, allowing user to monitor and make adjustments to the controlled system from anywhere. This enables remote management and control of the system, providing flexibility and convenience to the users.

By adapting and introducing Digital Twin into the industrial enterprise, it becomes possible to enhance visibility into the operation and condition of industrial equipment and other assets, as well as larger interconnected systems or subsystems. This improved visibility allows for better monitoring and management of these assets, leading to increased operational efficiency and effectiveness, improvement and optimization of production processes and assets through real-time data exchange and information. By integrating a Digital Twin into an industrial enterprise, it is possible to achieve better visibility regarding the operation and health of the industrial equipment, or any other assets, and larger interconnected systems or subsystems. (Arnautova, n.d.; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, n.d.)

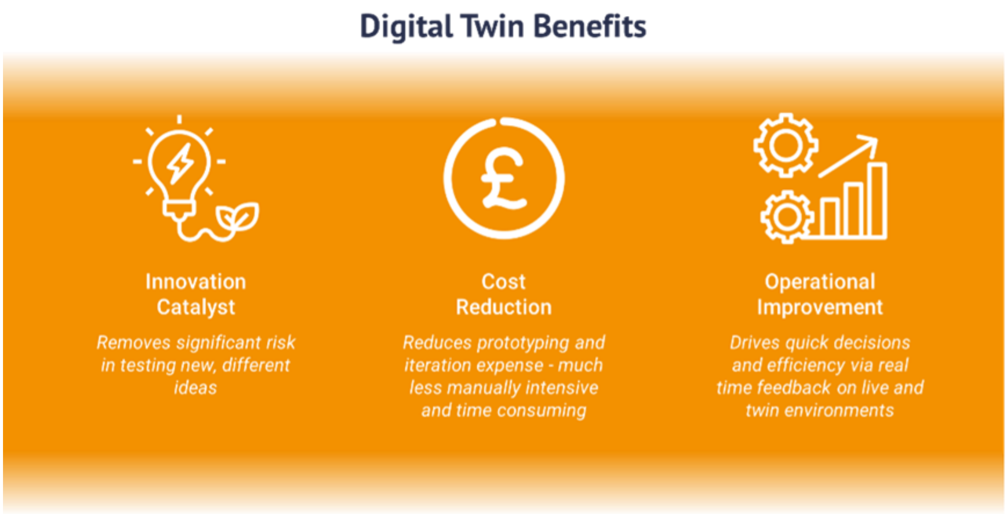

Figure 62 Digital Twin Benefits. (STL Partners, 2022)

Introducing new products to markets with reduced time

It is common knowledge that as new technologies get better, market conditions and variables change quickly. As a result, businesses and their customers are always looking for new products. With the assistance of a digital twin application, designers can learn and gain valuable knowledge how a new product will work and perform before it's finished. This makes it impossible for mistakes or failures to happen, which helps them deal with and meet new market demands and challenges.

Furthermore, leveraging a digital twin can enable the creation of a virtual representation of the product that closely resembles the real thing even before the physical product is completed. This would let the consumer try out the product before it is finished and experience the product virtually prior to its finalization.

Entering the marketplace ahead of competing companies is a crucial factor for businesses. Due to the lengthy and complex manufacturing procedures and frequent adjustments, this is frequently an issue. Therefore, the utilization of a digital twin provides designers a way to test products ahead of time and make necessary changes prior to the product’s launch.

A corporation may build a service or product faster by using a digital twin application, and the required time that it is needed for a corporation to introduce a product or service to the marketplace is significantly decreased when they implement a digital twin. (Arnautova, n.d.; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, n.d.)

Accelerating Risk Assessment and Production Time with a Digital Twin

During the initial phases of a product development, engineers and designers can test, evaluate, and verify it to find any flaws in the process before the product goes into production. They do this by simulating how the product will be made. Developers can mess with the system to make unexpected things happen, then look at how the system reacts and come up with ways to fix it. This new ability makes the production line more reliable, speeds up the making of new goods, and makes it easier to figure out what risks are.

A virtual prototype could save time and money by letting you test how your real copy will work in real life. In the digital world, fixing mistakes is much easier, cheaper, and faster than in the real world. Manufacturers can almost completely remove all risks from future production and make sure that the physical product works exactly as intended. Virtual versions are always controlling their physical models from afar with the help of sensors that gather data from many different sources. The engineers can predict possible problems by looking at the collected data, such as when a spare part is almost broken and needs to be replaced. By harnessing the capability to monitor and conduct virtual testing of the production process, manufacturers are able to ensure a safe and secure product is delivered each time. (Arnautova, 2022; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, 2022)

"What if" scenarios and Optimal Operation of the physical counterparts

The Virtual models of a Digital twin remain linked and connected to the physical ones. That interconnection between the physical and virtual counterparts allows for real-time analysis of the physical entity's performance in different scenarios and conditions and therefore produces in-time modifications to assure and verify that it functions exactly as designed in order to maintain optimal performance. The interface provided by the Twin allows the users to assess various operational scenarios and analyze "what if" different operational scenarios analyzing potential outcomes and determine the optimal actions required for implementation in the real application. This way, the virtual model allows an infinite number of simulation experiments and provides a reliable source of decision-making to be taken in the physical world with complete certainty that they are going to produce the desired outcome. (Arnautova, n.d.; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, n.d.)

Assets Maintenance

Today, assets create a lot of data that can be looked into and analyzed to figure out when a problem will happen in the future. The digital twin (DT) utilizes real-time data from IoT sensors and information from the physical asset and virtual model to predict breakdowns or maintenance events in advance. This helps reduce downtime and maintenance costs significantly. By analyzing the data, organizations can proactively identify and fix problems, optimizing maintenance activities and ensuring efficient system performance. With this feature, businesses can schedule tasks and activities for predictive maintenance more precisely in terms of time. This increases the productivity of the production line while reducing maintenance costs and downtime.

Using different modeling methods, the digital twin can predict how important business assets will be in the future and look at how any important problems that need to be managed will affect them. By taking advantage of these technologies, businesses can effectively predict any upcoming maintenance events and unavailability issues in their systems, allowing them to proactively address them before they become more serious problems. (Arnautova, 2022; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, 2022)

Combining Information Technologies

The digital twin (DT) leverages various information technologies to perform complex tasks more effectively.

Machine Learning: Machine learning techniques enable the DT to learn from data, identify patterns, and make predictions or recommendations. It plays a crucial role in analyzing and interpreting data collected from the physical twin, enabling the DT to provide valuable insights and optimize processes.

Simulations and Modeling: Simulations and modeling techniques are used to create virtual representations of the physical twin. These virtual models can simulate various scenarios, test different parameters, and evaluate the impact of changes in real-time, allowing for better decision-making and optimization.

Internet of Things (IoT): The IoT plays a significant role in the DT ecosystem by connecting physical devices and sensors to collect real-time data. The IoT enables the DT to gather information about the physical twin's performance, environmental conditions, and other relevant metrics, facilitating monitoring, analysis, and optimization.

Cloud Computing: Cloud computing provides the necessary infrastructure and resources for storing, processing, and analyzing large volumes of data generated by the DT. It offers scalability, accessibility, and computational power to handle complex tasks, enabling efficient data management and real-time analysis.

Big Data: The DT leverages big data technologies to handle and process the massive volume, velocity, and variety of data generated by the physical twin and other sources. Big data analytics techniques are applied to extract insights, identify patterns, and make informed decisions based on the collected data. By integrating these information technologies, the DT can perform complex tasks more effectively, improving productivity, efficiency, and decision-making in various domains such as manufacturing, maintenance, and process optimization.

For instance, Digital Twin applications can forecast what will happen by integrating sensor information, results of the simulation, and algorithms for machine learning. DT could use real-time simulations and cloud computing together to get powerful computing power. Additionally, by incorporating the IoT and big data analytics, the DT can gain access to data-driven insights that can inform better decisions. (Arnautova, 2022; ATRIA Innovation, 2021; Håvard et al., 2019; Ingenium, 2019; MJV Team, 2020; RF Wireless World, 2022)

Digital Twin applications in Refineries

The manufacturing industry has greatly benefited from the development of Artificial Intelligence , allowing for significant progress to be made in the areas of robotics and automation. Even though the demands for efficiency and dependability in large industrial processes are higher and exceed those in conventional manufacturing, this level of control and automation is still considered and recognized as cutting edge.

The optimization of processes, such as planning and scheduling, using machine learning and analytics, can be enhanced by reintroducing human involvement. This can be achieved through the application of visual analytics techniques, which enable the sharing of human expertise with the computer.

Improvements in various domains, such as decision making, design, and others, and particularly human comprehension within extensive datasets and complex models, have emerged as a result of the expertise and insights gained by experts. The integration of visual analytics tools is essential for bridging the gap between big data, artificial intelligence, and human involvement, enabling effective utilization of these advancements.

In reality, refineries are highly digital, with automated systems controlling and optimizing the vast majority of processes for decades (PID controls, linear multivariate optimizers). The use of rigorous models in the fields of design, simulation, and planning is widespread.

Many control systems are represented by a pyramidal structure this allows for a visual indication of the gradual abstraction achieved by layering more and more complex concepts. These models provide a systematic approach to problem-solving and decision-making, ensuring that all factors are considered and analyzed. They also enable designers and planners to identify potential issues and optimize their solutions before implementation.(Gandomi and Haider, 2015)

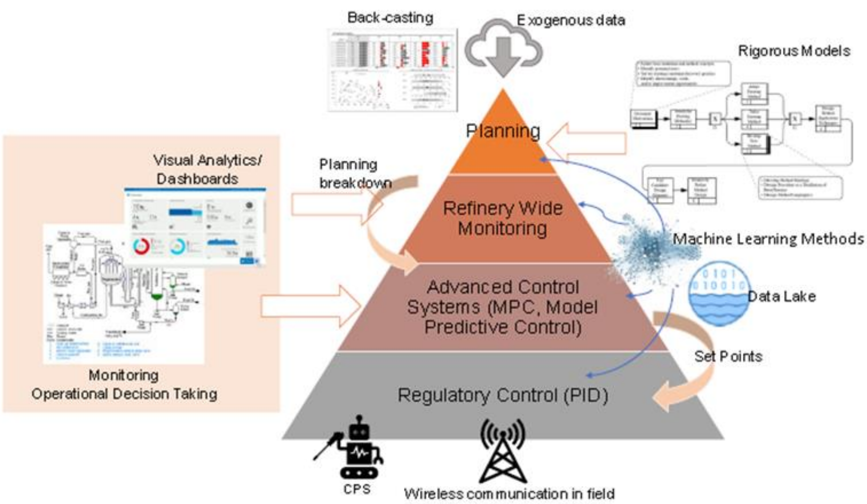

Figure 63. Control Pyramid endowed with data exploitation resources. (Olaizola et al., 2022)

The above depicted figure illustrates the different aspects of refinery control, operation, and monitoring. Many of these elements align with the principles of Industry 4.0. Similar to the implementation of MES (Manufacturing Execution System) and ERP (Enterprise Resource Planning) systems in manufacturing, modern refineries utilize automatic online optimizers that collect real-time data from various points throughout the facility. These optimizers are directly connected to information systems, enabling operational decision-making and strategic planning based on the gathered data. (Olaizola et al., 2022)

It's worth noting that ML models typically supplement rather than replace preexisting control and optimization infrastructure. These optimizers use machine learning algorithms to analyze the data and provide recommendations for process adjustments that can improve efficiency, reduce costs, and increase safety. This integration of advanced technology is becoming increasingly important in the highly competitive and rapidly evolving refining industry.

Data plays a crucial role in the functioning of a digital twin. The selection and integration of various sensors, gauges, RFID tags and readers, cameras, scanners, and other data collection devices are vital for capturing data on every component. Furthermore, it is essential for this information to be transmitted almost instantaneously to support real-time monitoring and analysis within the digital twin system.

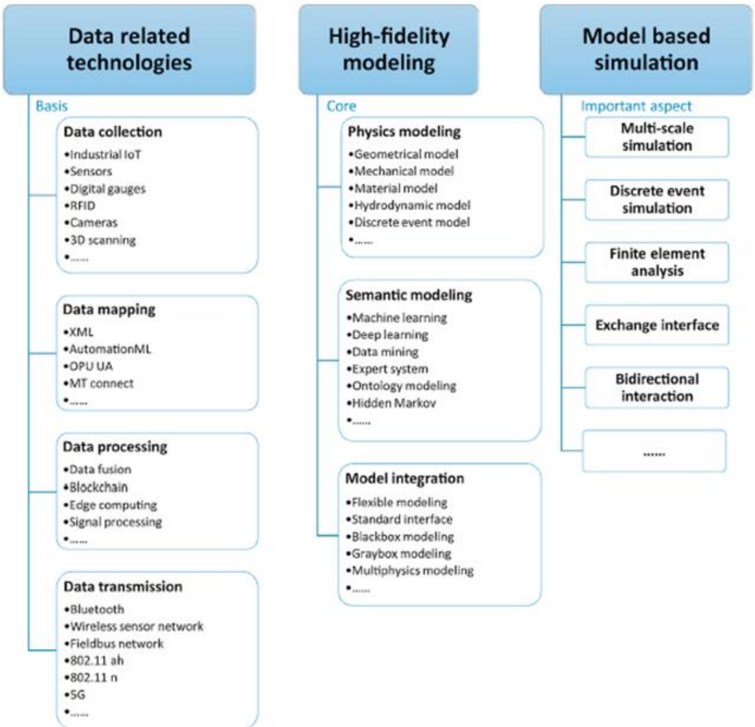

Figure 64. Technology trends and architectures for digital twin. (Liu et al., 2021)

But sending the data to the cloud server where the digital twin lives is hard and can be expensive because the data is so big, moves so fast, and has so many different types. Edge computing is a method that helps process collected information closer to where it's generated, reducing the strain on the network and lowering the chances of data leaks. With the introduction of 5G technology, data can be transmitted in real-time, enabling faster communication. To make sense of the data, it needs to be organized and combined from different sources, which is known as mapping and fusion. This allows for a better understanding of the system or process being monitored, leading to improved decision-making and optimization. (Liu et al., 2021)

The digital equivalent of something relies on a model as its foundation. The digital twin's models include both semantic data and physical representations of the system. Using AI techniques, semantic data models can be "trained" on a set of known inputs and outputs. To create accurate physical models, one must have a deep comprehension of all relevant physical properties and their interplay. Thus, high-fidelity modeling of the digital twin necessitates multi-physics modeling.

Digital twin simulation plays a vital role in the functionality of a digital twin. It enables a two-way real-time communication between the digital model and its physical counterpart. This technology finds extensive application in industries like manufacturing, aerospace, and healthcare, offering benefits such as process optimization, cost reduction, and performance improvement. By leveraging digital twin simulation, businesses gain the ability to anticipate and address potential issues before they manifest, thereby enhancing their competitive edge in the market.(Liu et al., 2021)

Numerous sectors have experienced significant benefits from the advancements in new generation information technologies (new IT). These technologies include the Internet, the Internet of Things (IoT), big data analytics, cloud computing, artificial intelligence (AI), and more. By leveraging these technologies, sectors across various industries have witnessed improvements in efficiency, productivity, decision-making, customer experience, and overall operational capabilities. The integration and utilization of New IT have opened up new opportunities and transformed the way businesses operate and interact with their customers and stakeholders.

The spread of Internet-enabled devices has led to a significant increase in data generation. This data comprises structured, semi-structured, and unstructured formats. To effectively manage, analyze, and extract valuable insights from this vast amount of data, big data analysis models and algorithms are employed. The storage and processing capabilities of cloud computing play a crucial role in handling the large-scale data processing requirements. By leveraging the robust infrastructure provided by cloud computing, organizations can efficiently organize, analyze, and mine raw data, uncovering valuable insights and driving informed decision-making. (Wang et al., 2020)

Meanwhile, self-learning Artificial Intelligence continues to advance its intelligence through data analysis. The product lifecycle in manufacturing generates a substantial volume of data, including structured, semi-structured, and unstructured formats, which collectively form big data. The Internet of Things (IoT) enables the automatic collection of real-time data from factories. By leveraging cloud-based big data analysis, manufacturers can identify bottlenecks in their processes and analyze the root causes and consequences. This empowers organizations to make data-driven decisions and drive improvements in efficiency and productivity.

By harnessing the insights derived from manufacturing big data, we can optimize our production methods and enhance our competitive edge in the global market. Valuable feedback obtained from analyzing manufacturing big data is applied throughout various stages, including product design, production, and maintenance and repair (commonly referred to as maintenance, repair, and overhaul or MRO). Moreover, there is a growing interest in exploring the synergies and convergence between the cyber and physical realms within the manufacturing domain. Understanding and leveraging these interactions can lead to further advancements and efficiencies in manufacturing processes.

The emergence of the digital twin facilitates the convergence of cyber-physical systems, enabling their seamless integration. A digital twin serves the purpose of creating a digital representation of a physical object, allowing for the modeling and simulation of its characteristics and behaviors in a digital environment. By utilizing sensing data provided to virtual models, it becomes possible to predict, estimate, and analyze dynamic changes in physical entities. Real-world objects can then respond in accordance with the simulation's plan. This closed-loop system, facilitated by the digital twin, holds the potential to enhance efficiency across the entire production cycle. (Alam and El Saddik, 2017)

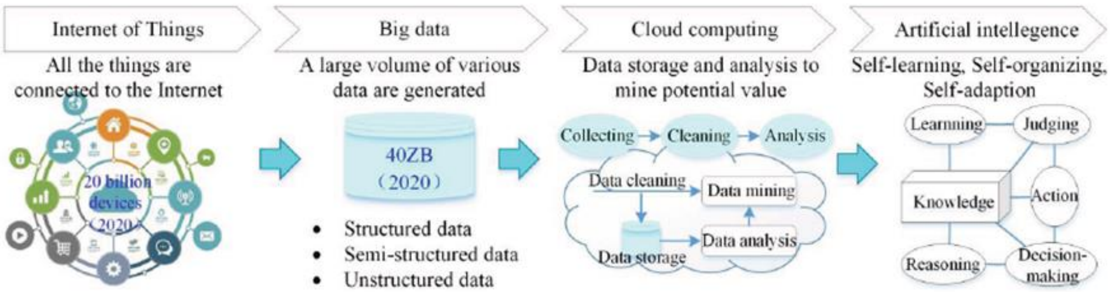

Figure 65. New IT and their applications. (Qi et al., 2018)

Digital twin technology enables real-time monitoring and adjustment, leading to less downtime and higher productivity. It also facilitates predictive maintenance, enhancing the overall efficiency of the production process. By utilizing data and insights from the digital twin, organizations can identify and address maintenance issues before they cause significant disruptions. This proactive approach optimizes maintenance schedules, reduces unexpected downtime, and maximizes the utilization of production resources, resulting in a more efficient production process.

Big data encompasses the vast amount of data collected during different phases of the manufacturing process, such as product design, production, maintenance, repair, and overhaul. It includes a wide range of information that provides insights into various aspects of manufacturing operations.

These phases from the manufacturing process create a lot of data, and the data themselves come in many different formats and come from many different places.(Qi and Tao, 2018) There is a lot of value hidden in the data. The following categories make up the bulk of manufacturing data:

- Real-time performance and operating condition data from Industrial IoT technologies in smart factories.
- Material and product data collected from themselves and service systems, providing information on performance, inventory, and context of use.
- Environmental data, such as temperature, humidity, and air quality.
- Information gathered by managers from various systems like CIS and MIS, including MES, ERP, CRM, SCM, and PDM. This includes data from CAD, CAE, and CAM systems.

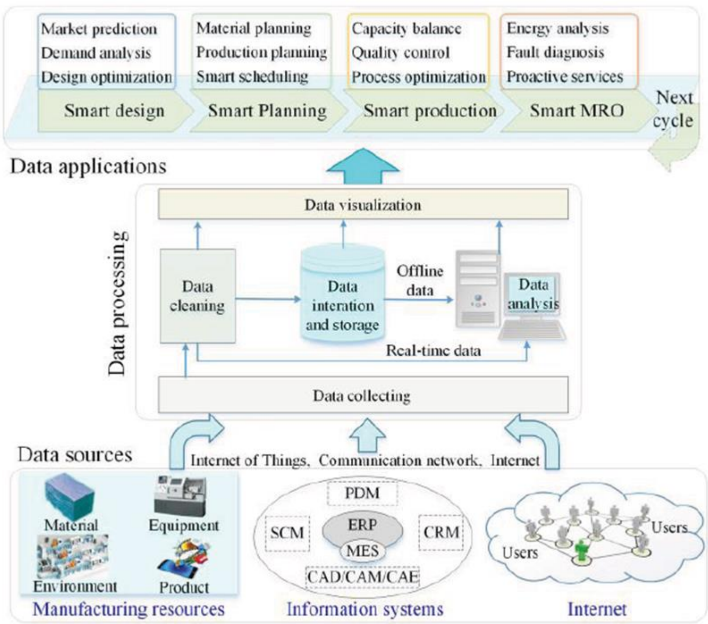

Figure 66. The sources, processing and applications of big data in manufacturing. (Qi and Tao, 2018)

This type of information includes things like the design plan, order processing, supply chain management, production schedules, sales and marketing plans, customer service operations, budgeting, and so on. Furthermore, there is data from the Internet, such as

- User feedback, preferences, and behavioral data gathered from e-commerce platforms and social media networks.
- Publicly available data obtained from open websites, including government and public service portals

However, raw data alone has limited intrinsic value. It requires a series of processes to unlock its true potential. Various methods and technologies such as IoT (utilizing smart sensors and RFID), API (application programming interface), SDK (software development kit), and web crawlers are employed to collect and gather the data. These techniques play a crucial role in the extraction and preparation of data for further analysis and utilization (Qi and Tao, 2018)

Before manufacturing data can be effectively utilized, it is necessary to undergo a cleaning process. This is because the data originates from diverse sources, exhibits varying scales, and is often contaminated with noise and other unwanted elements. Once the data has been cleansed, it is consolidated with other relevant data and stored for future use in manufacturing data repositories and exchange systems. Cloud computing plays a crucial role in enabling this storage and accessibility. Subsequently, advanced analysis techniques and tools, including machine learning algorithms and forecasting models, are employed to extract insights from the real-time or offline data, leveraging the power of cloud computing resources. (Qi and Tao, 2018)

Manufacturers can use the valuable information extracted from vast and complex data to gain insights into different stages of a product's lifecycle. This helps them make better decisions based on accurate information, improving their efficiency and making them more competitive. (Qi and Tao, 2018)

As big data becomes more prevalent, product design is transitioning from emphasizing creative inspiration and user experience to prioritizing empirical data and logical analysis. By looking at big data about how people use products and how the market is changing, designers can accurately measure what customers want and turn what customers say into product features and quality requirements. The product development process has been sped up and improved thanks to big data analysis.(Oluwasegun and Jung, 2020)

Smart production planners analyze the available resources and capacities, material data, technological parameters, and constraints before initiating the production process. By considering global data and understanding the interconnections between these factors, it becomes possible to develop a comprehensive planning program that effectively caters to the needs of the entire world. (Qi and Tao, 2018)

Manufacturers can better adjust to changing conditions by keeping an eye on their production in real time and using that information to fine-tune their operational control strategies. By analyzing big data, quality control and improvement are integrated throughout the entire production process, starting from the procurement of raw materials and extending to the shipment of the final product Real-time quality assurance measures include getting an early warning when there is a problem with the quality and finding the root cause of a problem quickly.

Finally, Big data's tremendous predictive ability alters the conventionally passive MRO mode. The collection and analysis of large amounts of data from smart devices or products enable the implementation of active preventive maintenance functions. This data is used to perform tasks such as monitoring the devices' health, identifying and fixing any problems that may arise, optimizing the products' operations, etc.

When big data analytics and AI-ML techniques are used with digital twins, they become even more important and give researchers new chances and challenges. Combining digital twins with big data analytics and AI-ML techniques can improve operations and maintenance through monitoring, predictive maintenance, quality assurance, decision support, and personalized services (Rathore et al., 2021; Zheng et al., 2018))

Big data is the data that, due to its heterogeneous variety and high velocity, and volume, differs from regular data, as illustrated in the following figure.

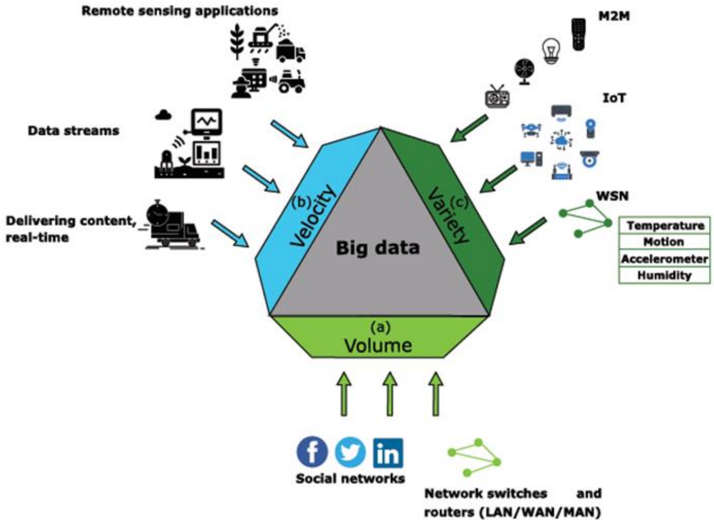

Figure 67 Big Data definition. (Rathore et al., 2021)

Big Data refers to the state-of-the-art tools utilized for handling and analyzing massive datasets in the context of upstream and downstream oil and gas operations. These datasets are generated in large volumes and cover a wide range of information throughout the industry's processes. (Brancaccio, 2020; Mehta, 2016).

Big Data refers to a wide range of data types, including structured, unstructured, and multi-structured data. Structured data is well-organized and follows a specific format, while unstructured data is text-heavy and lacks organization. Multi-structured data has diverse formats due to interactions between humans and machines. The term "Big Data" or "Big Data Analytics" is used to describe this approach, primarily focusing on the large size of the datasets involved.(Pence, 2014)

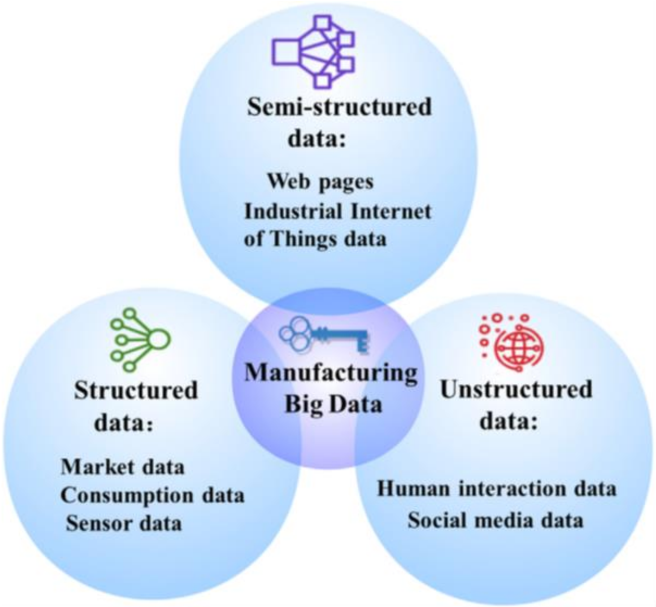

Figure 68 Sources of industrial big data. (Li et al., 2022)

The suitability of the data for utilization with big data tools is influenced by additional factors. IBM has referred to these factors as the “three Vs”: Volume, Variety, and Velocity, as mentioned in Pence's work (2014). (Pence, 2014)

Additional "Vs" have been introduced to offer a more comprehensive definition of big data. Veracity and Value are among the additional factors that contribute to the understanding of big data's characteristics. (Ishwarappa and Anuradha, 2015; Mehdi and Farshid, 2018)

The quantity of data or information is commonly referred to as "volume." Any data-recording sensor or instrument has the potential to generate such data. However, the storage, preservation, and analysis of this vast amount of data pose significant challenges. Numerous businesses possess extensive data archives, yet they often lack the computational capacity required to effectively handle this data. The primary purpose of Big Data is to offer tools for processing and analyzing the ever-increasing volumes of data. (Ishwarappa and Anuradha, 2015).

The rate at which data is transmitted and processed is commonly referred to as "velocity." It also pertains to the speed at which data is generated. The challenge with the velocity aspect is the limited number of processing units relative to the volume of data that needs to be processed. In the oil and gas industry, this velocity characteristic becomes even more apparent due to the complexity of various petroleum engineering issues. Processing a large volume of data generated for a complex problem is beyond the capabilities of a single person, leading to significant delays and uncertainties. In the oil and gas sector, there are numerous scenarios where prompt and real-time data processing is crucial (Ishwarappa and Anuradha, 2015; Mehdi and Farshid, 2018; Mehta, 2016)

The various types of data that are generated, stored, and analyzed are collectively referred to as "variety." Due to the existence of different sensors and devices for data recording, the generated data can come in diverse sizes and formats. It can be in the form of text, images, audio, or video. From a technical perspective, data classification can be carried out as structured, semi-structured, or unstructured data, depending on its organization and format. (Mehdi and Farshid, 2018; Sumbal et al., 2017).

SCADA systems, supervising and controlling surface or underground facilities and installations, drilling data, and production data play a significant role in generating the majority of oil and gas-related data. These sources often provide time series data collected over specific time periods. In addition to these sources, reports for assets, risk, and project management serve as additional structured data sources. Well logs, daily written reports of drilling activities, and CAD drawings are examples of unstructured data sources commonly found in the oil and gas sector. Semi-structured data can be derived from modeling and simulation processes. Collectively, these sources contribute to the diverse data landscape within the oil and gas industry. (Mehdi and Farshid, 2018; Mehta, 2016)

In the oil and gas industry, a range of experimental and computer simulation techniques are employed to generate data for further analysis. These data are considered semi-structured and can be effectively utilized with big data tools. The processed data derived from these sources offers valuable insights and information that can be utilized by the oil and gas industry to enhance drilling operations, optimize production processes, and improve overall operational efficiency.(Mehdi and Farshid, 2018)

"Veracity" refers to the quality and reliability of data available for analysis and decision-making purposes. It involves distinguishing between accurate and erroneous data. This aspect is crucial because outdated or inaccurate data can significantly impact the speed and accuracy of data analysis. To ensure reliable outcomes, the generated data needs to undergo professional and effective processing and filtering before being used for analysis. This step is essential to ensure that the data used in analysis is trustworthy and dependable.(Sumbal et al., 2017)

The "value" aspect of Big Data holds great significance. The financial return on investment for Big Data analytics services and infrastructure is a crucial consideration. Big Data analytics enables the examination of vast datasets to uncover underlying patterns and helps engineers anticipate potential problems. Having the ability to predict equipment performance and identify potential failures before they occur can provide a company with a competitive advantage and contribute value to the business. By leveraging. (Sumbal et al., 2017) Big Data effectively, organizations can gain insights that lead to improved decision-making and enhanced operational efficiency, ultimately adding value to their overall operations.

There is one more significant characteristic that should be taken into account when applying big data in addition to these five Vs. "Complexity," the complex nature of the issue for which data collection is being done, is a crucial characteristic (Khvostichenko and Makarychev-Mikhailov, 2018). Finding the overall trend in large data sets that are the result of complex computing problems requires sophisticated techniques.

The use of Big Data analytics can provide organizations with powerful insights into their operations, enabling them to make informed decisions about the future.

The provided diagram showcases the key attributes of Big Data.

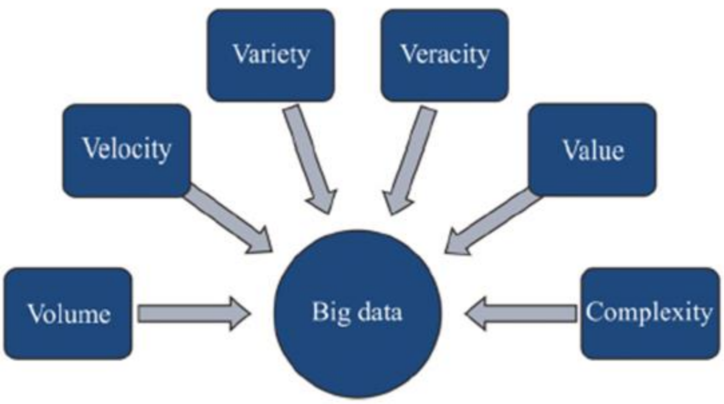

Figure 69. Big Data Characteristics. (Mehdi and Farshid, 2018)

Artificial Intelligence and Machine Learning – Deep Learning

Artificial Intelligence (AI) serves as a digital representation of the three cognitive skills humans possess: Self-correction, Learning, Reasoning. Digital learning involves establishing a set of rules that transform real historical data into actionable information through the utilization of algorithms. Digital reasoning focuses on selecting the appropriate rules to achieve desired outcomes, emphasizing decision-making based on these rules. (Rathore et al., 2021)

In contrast, digital self-correction entails leveraging the results obtained from learning and reasoning repeatedly. It is an iterative process wherein the outcomes are used to continually enhance and refine a program's predictive capabilities. By continuously learning and leveraging previous experiences, Artificial Intelligence systems improve their ability to make accurate predictions. (Rathore et al., 2021; Sircar et al., 2021)

The approach used by each Artificial Intelligence model to develop an intelligent machine capable of performing tasks that typically necessitate human intelligence varies. While most AI systems rely on machine learning, including deep learning, data mining, or other rule-based algorithms, some also incorporate logic and knowledge. Currently, deep learning and machine learning are among the most widely utilized techniques in the field of AI (Rasheed et al., 2020; Rathore et al., 2021)

Indeed, distinguishing between artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques can be quite challenging, as they are closely related but have distinct characteristics.

Machine Learning: ML is a subset of AI that focuses on the development of algorithms and models that allow machines to learn from data and improve their performance without being explicitly programmed. ML algorithms can analyze and extract patterns from large datasets to make predictions or decisions This means that the more data we can collect, the better we can make decisions, and predict outcomes in the future.(Elijah et al., 2021)

Machine learning can be

1) Supervised learning, that instructs a model how to categorize things or predict the future using sets of data with labeled outputs;

2) Unsupervised learning, that groups or clusters data based on sets of data without labels; and

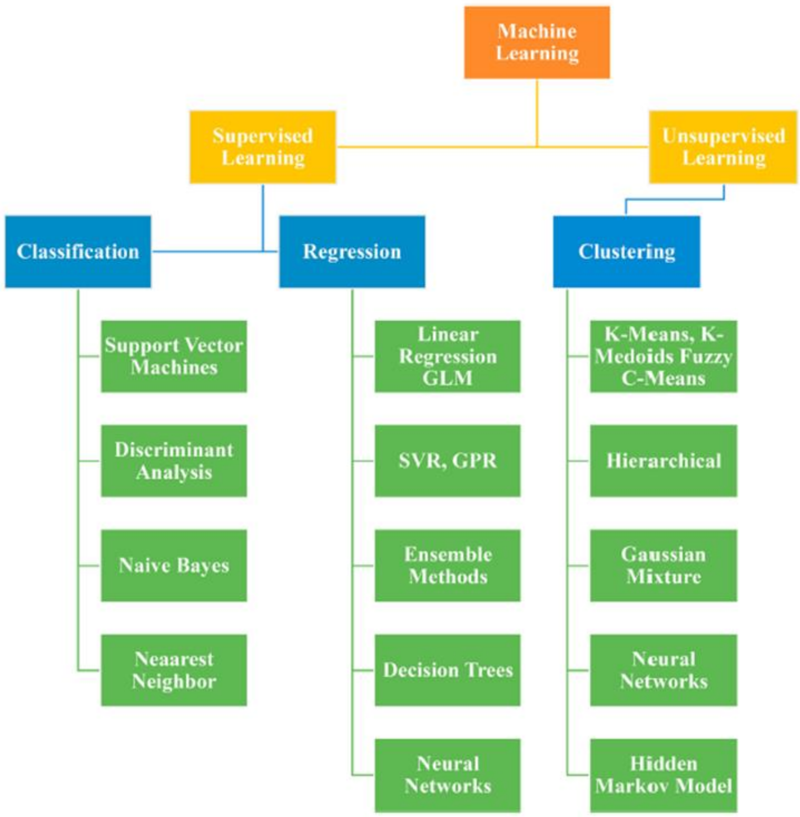

Figure 70. Steps involved in Machine Learning Problems. (Sircar et al., 2021)

3) Reinforcement learning, that employs labelless data records but provides input to the Artificial intelligence system after it completes specific actions.

Deep Learning: DL is a specific branch of ML that emulates the workings of the human brain's neural networks. It involves training artificial neural networks with multiple layers to learn hierarchical representations of data. DL has been successful in tasks such as image and speech recognition, natural language processing, and autonomous driving. (Elijah et al., 2021). Deep learning is a highly effective and widely used tool for machine learning tasks, especially when the amount of data available is large.

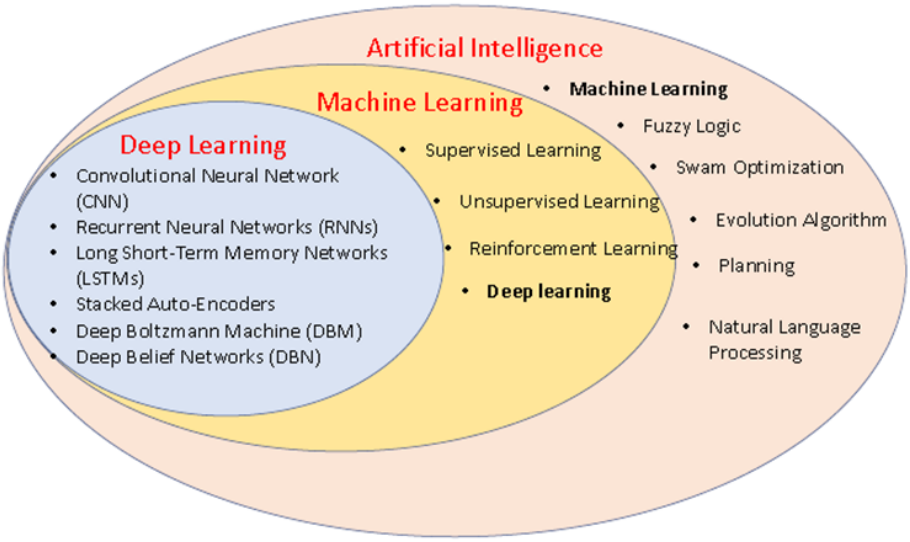

Figure 71 Branches of Artificial Intelligence. (Elijah et al., 2021)

Artificial Intelligence: AI refers to the broader concept of creating intelligent machines that can simulate human intelligence and perform tasks that typically require human intelligence. It encompasses various techniques, including ML and DL. While ML and DL are subfields of AI, AI can also include other techniques beyond these two, such as expert systems, rule-based algorithms, and symbolic reasoning. In summary, AI is the broad field encompassing the creation of intelligent machines, ML is a subset of AI focusing on algorithms that learn from data, and DL is a specific approach within ML that uses deep neural networks to learn hierarchical representations of data. (Elijah et al., 2021)

Real-time monitoring of physical objects is facilitated by connecting the physical environment to its virtual representation through the use of IoT (Internet of Things) devices. These devices enable the collection of real-time data necessary for creating a digital twin of the physical component. By employing sensors and actuators, the physical component can be optimized and maintained more efficiently. The integration of IoT devices allows for a continuous stream of data from the physical environment, enabling real-time monitoring and analysis. This data can be used to create a digital twin, which is a virtual replica of the physical object or system. The digital twin provides a detailed and dynamic representation of the physical component, allowing for better understanding, analysis, and optimization of its performance. (Oluwasegun and Jung, 2020; Zheng et al., 2018)

Because the IoT data generated from IoT devises as mentioned above are massive in volume and variety, (Gandomi and Haider, 2015) in industrial processes, making the use of big data analytics crucial for creating and utilizing digital twins effectively. Conventional methods for monitoring and analyzing industrial processes may not be sufficient to identify potential problems or optimize performance. The complexity and scale of these processes often require a more comprehensive and data-driven approach.

On the other hand, these problems are easy to spot in the data that has been collected, which makes industrial processes more effective and smarter. But in the industrial and DT fields, this huge amount of data needs to be handled with sophisticated techniques, architectures, frameworks, tools, and algorithms. In order to make effective use and to leverage IoT data and create a successful digital twin application, companies need to invest in developing appropriate big data analytics strategies that can help them identify potential problems, improve productivity, and make industrial processes more efficient. (Rathore et al., 2021)

According to Wang et al. (2020), cloud computing is often considered the optimal platform for processing and analyzing big data. It offers scalable and flexible resources for handling large volumes of data efficiently. Moreover, to create an intelligent digital twin (DT) system, cutting-edge AI techniques must be applied to the collected data. These advanced AI techniques enable the extraction of valuable insights and the development of intelligent functionalities within the DT system. (Wang et al., 2020).

The capability of a Digital Twin (DT) to detect the optimal process strategy, resource allocation, safety concerns, and faults is crucial for predictive maintenance, health status prediction, and real-time decision-making. By utilizing actual sensor data and/or virtual twin data, the DT can perform tasks such as optimizing planning, process control, scheduling, and making informed decisions in real-time. This empowers to enhance operational efficiency, improve maintenance practices, and respond promptly to changing conditions or potential issues detected by the DT. (Alam and El Saddik, 2017; Oluwasegun and Jung, 2020; Zhang et al., 2020)

IoT devises plays a fundamental role in collecting vast quantities of data from the physical world. This data is then utilized as input for AI models to generate digital twins. The digital twin, in turn, enables the optimization of various industry processes. Digital Twin (DT) technology serves as a means of connecting and comprehending both the physical and virtual realms through the application of artificial intelligence (AI). The relationship between IoT, big data, AI, and digital twins is illustrated in the accompanying figure, illustrating their interconnections and dependencies.(Rathore et al., 2021)

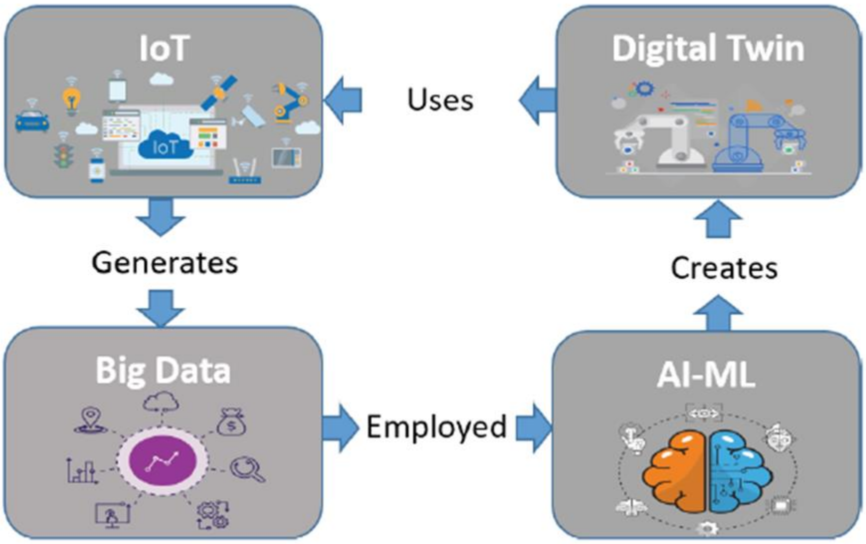

Figure 72 Relationship between IoT, big data, AI-ML, and digital twins. (Rathore et al., 2021)

In the industrial sector, the Industrial Internet of Things (IIoT) and emerging sensor technologies are deployed to develop digital twins of physical components within industrial settings. By harnessing big data analytics, organizations can detect potential issues, enhance productivity, and optimize industrial processes. The Digital Twin (DT) technology serves as a means of utilizing artificial intelligence (AI) to establish connections and facilitate comprehension between the physical and virtual counterparts. This integration of IoT, big data, AI, and digital twins exemplifies their interdependent relationship, collectively contributing to improved efficiency and performance in industrial operations. Information and data is derived from a real, physical object, such as a process unit, or its virtual equivalent in a DT environment. (Rathore et al., 2021)

Such information can also be used for AI-powered fault diagnosis for the equipment and manufacturing process optimization during the operation cycle. This information can be used to gain real-time insights on the performance of production and can be used to adjust accordingly.

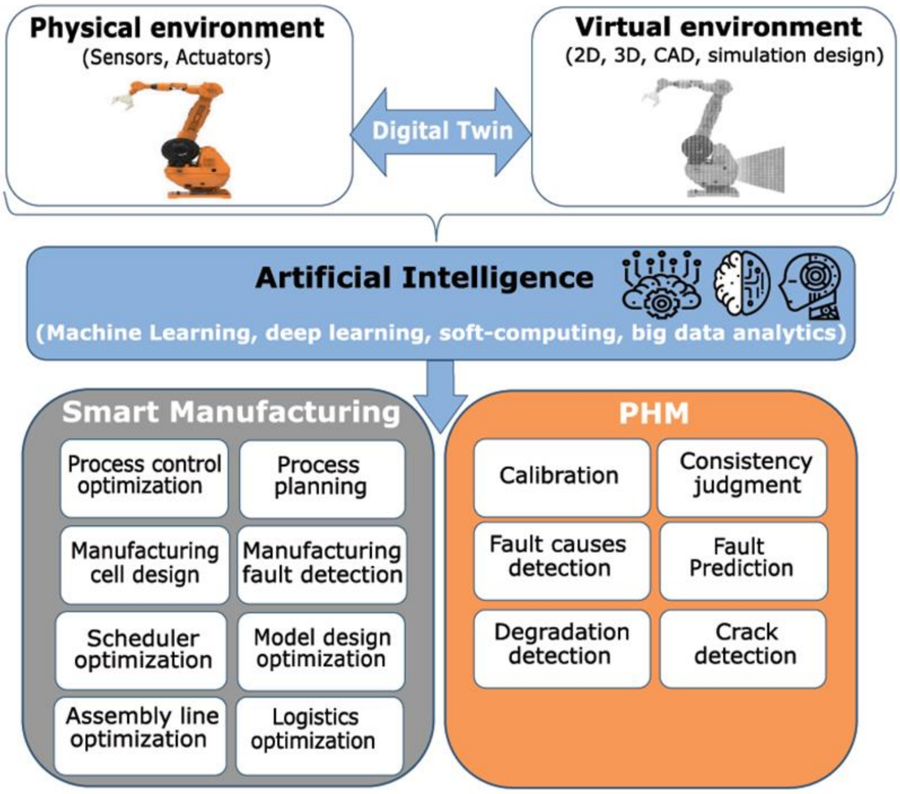

Figure 73 DT Based smart manufacturing using big data analytics and AI-ML. (Rathore et al., 2021)

A product's performance deteriorates with continued use, which could result in malfunctioning. In all industries, prognostics and health management (PHM) are therefore essential. The PHM process entails consistent health monitoring and the estimation of a product's remaining useful life based on the information produced by the sensing devices on the equipment. Then, based on the collected data and utilizing them, it makes recommendations for design guidelines for prompt maintenance actions and uses big data analytics tools and models of Artificial Intelligence to evaluate and predict problems. Industries can constantly improve not only their production but also their maintenance processes with DT-based PHM, which enables them to save time, cut costs, and boost productivity.(Rathore et al., 2021)

All of these activities contribute to lowering maintenance costs, raising operational effectiveness, reducing downtime, and enhancing customer satisfaction.

PHM that is based on DT is the second most important use of DT. It helps businesses optimize their production and maintenance processes to save time, cut costs, and boost productivity. It also helps to minimize downtime, increase operational efficiency, reduce maintenance costs, and improve the customer experience.

A useful digital twin can only exist if its functionality is very close to that of its physical twin. The most important thing to think about when judging digital twins is how accurate they are. To determine the improvement achieved through the use of a digital twin in optimizing an assembly line, a comparison can be made between the time and number of actions necessary to complete a full element or accomplish a primary task or goal. This evaluation involves measuring the time and actions required when utilizing the digital twin and then conducting a similar assessment without the digital twin. By contrasting the results of these two scenarios, the impact and effectiveness of the digital twin in streamlining the assembly line can be quantified, providing a clear indication of the improvement achieved. (Rathore et al., 2021),

The effectiveness of a digital twin (DT) is significantly influenced by the accuracy of the AI or machine learning (ML) techniques used. Several factors, such as the robustness of the ML model, feature selection process, and volume of training data, can greatly impact the results of the DT. When constructing a DT-based system that incorporates ML techniques, it is essential to select the most accurate and efficient model. The choice of other technologies for DT development, including IoT, edge computing, and cloud computing, should follow the same methodology. These technologies should be evaluated based on their compatibility with the ML model, their ability to handle data processing and storage requirements, and their capability to support real-time data analysis and decision-making. (Rathore et al., 2021)

Additionally, to ensure that the selected model will be accurate enough, we must take into consideration all of its parameters, related to its architecture, training process, and data usage. The number of layers and neurons in the model's architecture since it is playing a vital role in its learning capacity and complexity. The optimizer used to train the model affects how it learns and updates its parameters during the training process.

A diverse and representative dataset that covers various scenarios and variations in the target problem domain is essential for training a robust and accurate model. Considering these parameters and making informed decisions when selecting the model architecture, optimizer, and training/validation data contribute to ensuring that the chosen model is accurate enough for the desired application. This attention to detail increases the chances of building a reliable and effective digital twin system that can deliver valuable insights and support decision-making processes.

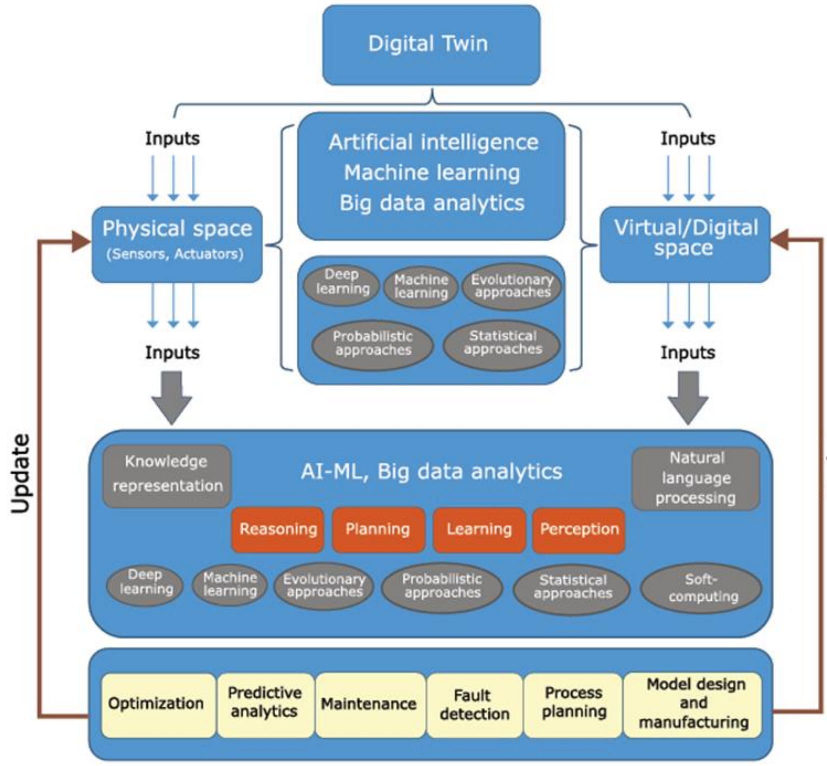

Figure 74 Overall data flow framework for DT using big data analytics and AI-ML. (Rathore et al., 2021)

In the digital twin framework, an initial AI model is applied to the data generated by the physical twin to create the virtual model. Once the digital twin is established, additional AI models come into play, utilizing data from both the physical and virtual twins. These AI models assist in various areas such as optimization, interactive production planning, and Prognostics and Health Management (PHM). By leveraging data from both twins, AI models can detect faults, optimize processes, facilitate predictive maintenance, and aid in troubleshooting. The outcomes and insights generated by these AI models can be used to update and enhance both the virtual and physical twins, further improving their accuracy and effectiveness. The integration of

AI models within the digital twin ecosystem enables continuous monitoring, analysis, and optimization of the physical system. The data-driven capabilities provided by these AI models enhance decision-making, promote efficiency, and contribute to the overall performance improvement of industrial processes.(Rathore M. et al, 2021).

Chemical Process Digital Twin

A digital twin model of a chemical process should incorporate computational or analytical models necessary to describe, comprehend, and predict the states and behaviors of the process. These models may encompass principles such as integrated steady-state, hydraulics, and dynamics, relying on mathematical expressions like algebraic equations or complex differential equations. .(Gao et al., 2022). Figure 78 illustrates the components of a digital twin for a chemical process.

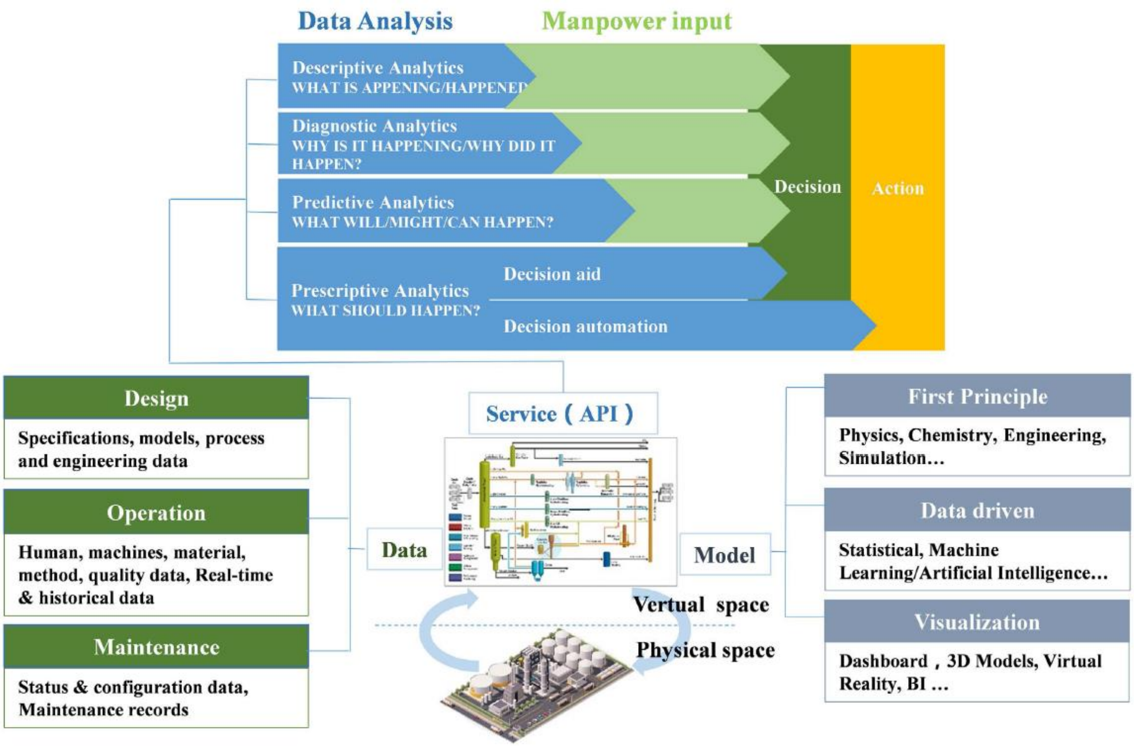

Figure 75. Components of chemical process digital twin. (Gao et al., 2022)

It may involve data-driven models based on artificial intelligence, machine learning, and statistics. Additionally, a 3D model or augmented reality (AR) model can be included to enhance understanding of the plant's operations.

In general, a digital twin model should exhibit accuracy, computational efficiency, and sufficient physics to facilitate timely decision-making. These factors significantly influence the applicability and differentiation of physics-based models for digital twins compared to other applications, such as safety verification or performance modeling, where high accuracy may take precedence over runtime efficiency due to their safety-critical nature (Gao et al., 2022; Wright and Davidson, 2020)

A comprehensive digital twin must encompass data throughout the entire asset lifecycle and value chains of the refinery, spanning design, operations, maintenance, and strategic business planning. This includes both historical and real-time data of high accuracy.

Furthermore, a digital twin of a process should provide application interfaces for advanced analytical purposes. Four types of analytics are commonly employed: descriptive (what happened?), diagnostic (why did it happen?), predictive (what will happen?), and prescriptive (what should you do?).

Leveraging the digital twin, operators can conduct "What if?" and "What's best?" scenarios to identify and select optimized and profitable strategies. They can then assess the suggested strategies to understand their impact and make informed evaluations.

Operators then can look at the suggested strategies to see how each one will affect them and to evaluate accordingly.

Unit operations within a refinery comprise technologies utilized to address operational challenges. These operations can be classified into transfer processes, including momentum transfer, heat transfer, mass transfer, and reactions(Grossmann and Westerberg, 2000)

A chemical process consists of interconnected operational units that collaborate and function together. It exhibits a multi-scale hierarchical and functional structure across time and space, as depicted in Figure 79 and illustrates the scope and hierarchy of a chemical digital twin, highlighting three dimensions:

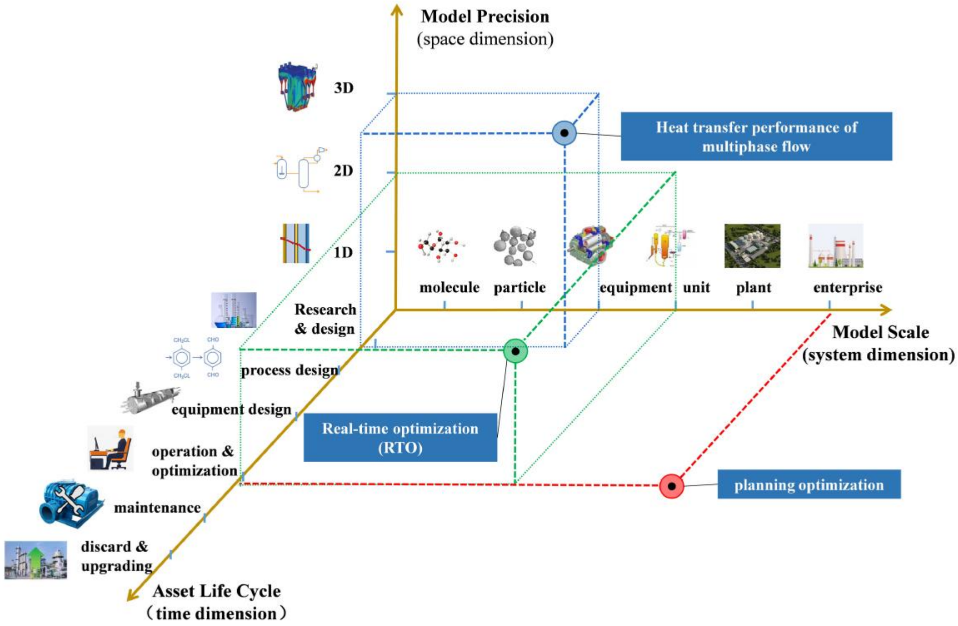

Figure 76. Scope and hierarchy of chemical digital twin. (Gao et al., 2022)

- System dimensions that encompass multi-scale thermodynamic behaviors.
- Space dimensions representing geometric model precision from 0D, 1D, 2D, to 3D.
- Time dimension reflecting the asset lifecycle.

Additionally, there is a model scale that corresponds to time, showing how chemical processes or model objects evolve over time. It shows how chemical processes change over time or how model objects change over time as shown in the following figure.

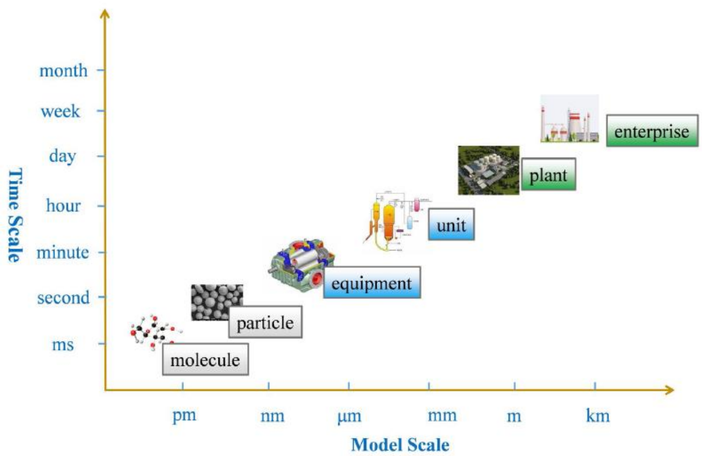

Figure 77. Chemical process of multi scale in time and space. (Gao et al., 2022; Grossmann and Westerberg, 2000)

In general, the relationships between chemical digital twins (DTs) in systems can be categorized into four main groups based on their primary functions.

Digital twins at the equipment level primarily concentrate on critical and high-value equipment, such as compressors (due to the significant financial cost associated with breakdowns, spare parts, and maintenance), large pumps (due to the high expenses related to spare parts and maintenance), and heat exchangers (which can impact yield). These DTs evaluate and assess the performance and availability of the equipment across past, current, and future operational stages.(Gao et al., 2022)

Digital twins at the unit level focus on fundamental chemical unit operations, including cracking, olefin reactors, and distillation. These DTs are utilized in areas of high value and potential returns, such as process analysis, asset condition monitoring, control systems optimization, and process optimization.(Gao et al., 2022)

Digital twins at the plant level create a digital replica of an entire plant. At this level, the focus is on optimizing energy consumption, refining and bulk chemical production planning, as well as scheduling for special chemical production. These DTs enable efficient decision-making and optimization in these areas. (Gao et al., 2022)

Digital twins at the enterprise level are a significant emerging field. This model can efficiently deliver actionable information to the executive level while quickly analyzing the profit opportunities of businesses.

Moreover, it possesses the capacity to enhance profitability and enhance customer satisfaction, while also optimizing the utilization of networks pertaining to plants, transportation, and storage facilities.(Gao et al., 2022)

The individual equipment-level twins are merged to form a cohesive unit-level twin, which represents the combined functioning of these equipment units. By integrating these unit-level twins, the plant-level twin is created, offering an accurate representation of the overall operation encompassing all equipment components and operational units forming the system. It is crucial for the engineering, manufacturing, and design data of the equipment-level twin to be precise and reliable. (Gao et al., 2022)

In the process industry, two key value chains, namely the supply chain and the asset life cycle, converge during the production process. These value chains are interconnected and integral to the overall operations of the industry.. (Bamberg et al., 2021; Gao et al., 2022)

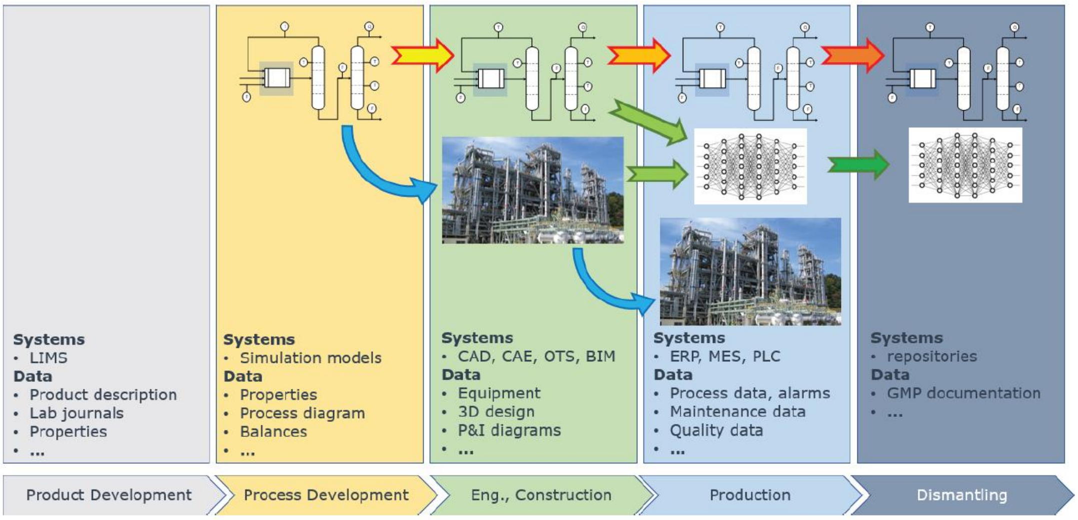

Figure 78. Elements of the digital twin in the course of the vertical asset life cycle. (Bamberg et al., 2021)

The objective of the DT System is to serve as a precise depiction of an asset throughout its entire operational range and lifespan. Its primary goals include enhancing engineering and project implementation, offering comprehensive visibility across the value chain, facilitating seamless transition to operational phases, enhancing operational and maintenance efficiency, and promoting sustainability in terms of health, safety, and environmental aspects. (Gao et al., 2022) The following table adapted from Gao et al, 2022 and their works with title *"Process Digital Twin and its Application in Petrochemical Industry"* and mentioned to application and benefits in during the stages of development, engineering and operation.

Digital Design	Application & Values of Digital Twin
“Digital R & D phase”	*“Reduce experimentation time & cost* *Optimize process & product design* *Streamline formulation-to-manufacturing* *Accelerate innovation”*
“Digital engineering phase”	*“Optimize CAPEX and time to market* *Optimal unit operation design* *Optimal process design & Debottleneck* *Virtual commissioning & Operator training”*
“Digital operation phase	*“Exploit plant data, leverage high fidelity process models online* *Optimize OPEX by mirroring, soft-sense, forecast & optimize* *Digital twin tools for operation excellence, decision support & prescriptive maintenance”*

Table 6 Application and Values of Digital Twin in digital process design. (Gao et al., 2022)

The development of digital twin ideally takes place during the preliminary investigation phase to assess the viability of the asset. It is employed and enhanced throughout the asset's design, construction, and commissioning stages. The digital twin aids in achieving the most efficient design for the asset and in training the personnel responsible for its operation. It operates in the present by simulating the actual plant, incorporating comprehensive historical data and an accurate projection of its future capabilities. (Gao et al., 2022)

Digital Twin Maturity

In order to increase operating margins, the petrochemical industry is constantly working to develop a more reliable digital twin operating model. The static information model that currently exists can be upgraded to a dynamic model known as a "digital twin". It could help operators show that the investment will pay off over time. An important step in this transformation process has been accepting information modeling. Operators and organizations can improve the consistency and efficiency of their design, construction, and operation by using and developing digital representations of assets.(Bane, 2017; Kharche, 2022; Nhede, 2018)

The digital twin is more than just a tool or method you can use to improve how your business works. The digital twin model could come from the development of the information model and its many layers. The evolution at each stage gives stakeholders across the lifecycle more power, which also makes it easier for them to exercise better control, make better plans, and perform better. But before tying the engineering information model to sources of dynamic operating data, this integration needs to be carefully planned and executed to ensure that the gathered data is accurate and unique and that it can be effectively used to inform and aid decision-making functions. Additionally, it is important to establish clear protocols for data sharing and communication among stakeholders to maximize the benefits of this integration. (Kharche, 2022)

The level of information or data availability for an asset and its environment is frequently misunderstood as the maturity of a digital twin. However, the various levels of insights deduced from the data model can be used to categorize the maturity of digital twin.

The digital twin is a single place where all information and data about an asset can be stored. In actuality, a digital twin's main objective is to produce a unique data and information for an asset. This means that having access to all data or information is the first step toward the digital twin becoming mature. By making a digital twin, organizations can learn important things about how their assets work and behave, which helps them improve operations and cut costs. Additionally, digital twin applications can also perform and operate for predictive maintenance functions and simulations in order to improve asset reliability and performance. (Bane, 2017; Nhede, 2018)

Once this information is available, different types of analytics can be done, such as predictive, prescriptive, transformative, and cognitive analytics. These analytics' data insights can then be connected to use cases and business outcomes.

Given that plants can last for more than 30 years, plant operators will stand to gain the most from the adoption of DTs. By reducing asset downtime and increasing availability, DT can help improve services, which will eventually boost the profit margin. When making a DT framework, you need to think carefully about the level of DT maturity because business outcomes are based on this level. The complexity of the DT framework increases with maturity. The following figure shows a typical digital twin against maturity:

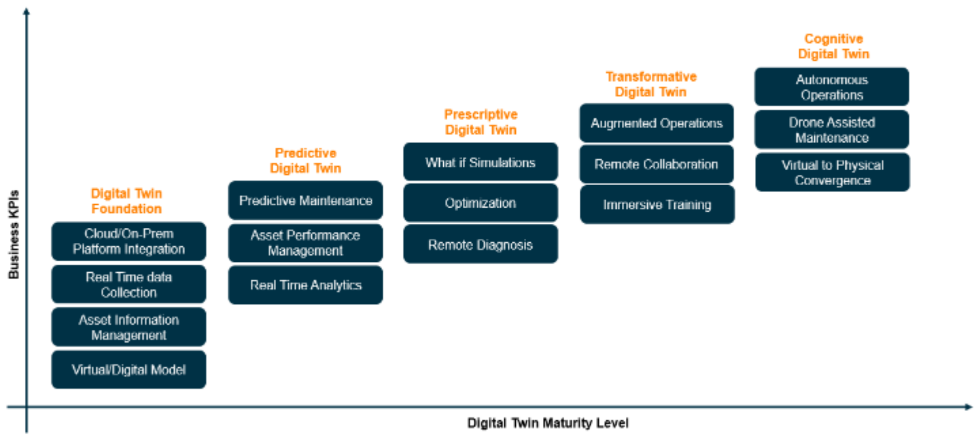

Figure 79. Digital Twin Maturity Level. (Kharche, 2022)

All stages of the plant lifecycle can be applied to digital twins and their methodologies. The data and insights are richer the sooner a project uses digital twins. The uses of digital twins are numerous. Different stakeholders engage with digital twins from various angles and derive value in various ways. For instance, engineers use digital twin functions for simulation and optimization of the performance in complex equipment systems or processes, many times in a virtual and risk-free environment, while business leaders leverage them to make data-driven decisions and improve operational efficiency. Moreover, digital twin also enables engineers to conduct and explore different scenarios in a virtual and risk-free environment.

Digital Twin and the Autonomous Refinery

A digital model of the physical system, called a digital twin, is developed to support the design, operations functions, and maintenance of the actual system with greater insight than has previously been possible by expanding the concept to all stages over a product life cycle. (Cimino et al., 2019)

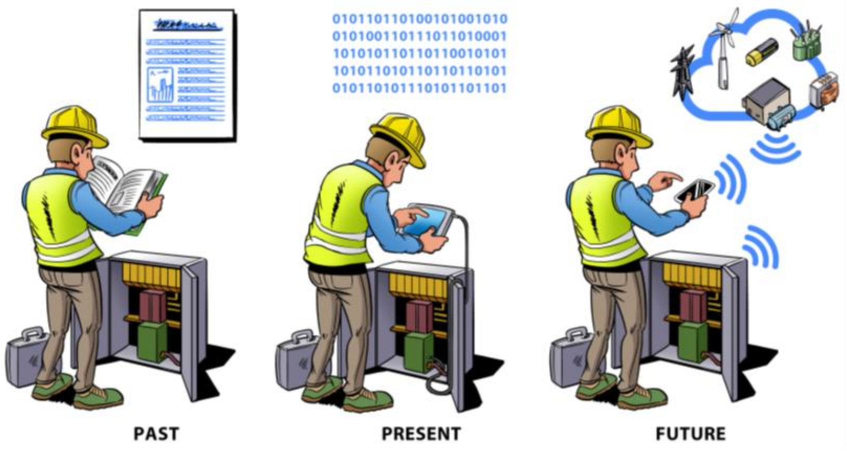

Figure 80 In contrast to classical maintenance, the digital twin provides insight into the behavior of the entire system. (Palensky et al., 2022)

The digital twin technology has been increasingly adopted by various industries, such as aerospace industry, petrochemical industry, automotive industry, and healthcare industry , to improve product performance and reduce costs. It allows for virtual testing and simulation of the physical system before actual implementation, leading to a faster time-to-market and better decision-making.(Dhole, 2019; Lu et al., 2020)

The digital twin is highly useful in many contexts involving complex operations, as a precise, trustworthy, and timely decision-making aid for stakeholders at all levels, from maintenance crews and planning engineers to substation bay controllers. (Palensky et al., 2022) The digital twin technology provides the ability for real-time monitoring and analysis of physical assets, which can lead to increased efficiency and reduced downtime. Its potential applications range from manufacturing and construction to energy and healthcare sectors.(Beck, 2019)

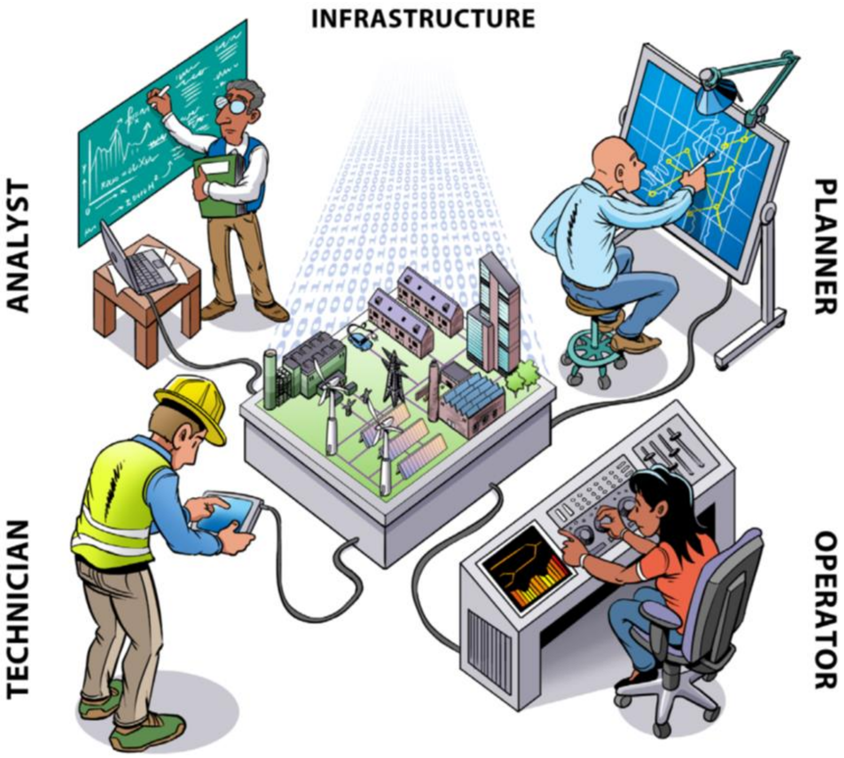

Figure 81 Uses of digital twin in analytics, maintenance, real-time operations and planning. (Palensky et al., 2022)

Digital twins allow companies to run real-time risk analyses, health assessments, and what-if scenarios; train employees in an augmentative or virtual interactive, risk-free environment, and detect faults early, before the control limits of the equipment's operational envelope are reached. The objective is to explain the digital twin, its advanced capabilities, and how oil and gas operators can use it to gain a competitive edge. Using digital twins also means that oil and gas operators can optimize production by fine-tuning existing processes, predicting future performance, and reducing downtime. (Wanasinghe et al., 2020)

By simulating how physical assets work, digital twins give operators a better and comprehensive understanding of the situation status and help them to provide improved and more effective decisions. Digital twins can help teams work together better by giving them a unique operational data and letting them do inspections and audits virtually. By leveraging the power of digital twins' operation, refinery operators can enhance their operational efficiency, reduce risks, and drive better business outcomes. (Sircar et al., 2022)

A digital twin is a dynamic, digital model which is an exact replica of the physical model and copies and represent the performance and operation of a physical object or process function over its entire lifecycle, which includes the following phases like design phase, engineering phase, construction, commissioning, and operation phase. These digital replicas allow oil and gas operators to simulate various scenarios and optimize processes, leading to improved decision making and resource utilization. Additionally, digital twins enable predictive maintenance, minimizing downtime and reducing operational costs. (Pietri, 2020)

The digital twin is constantly changing in order to match the changes in its real-world counterpart. This creates a closed-loop feedback system in a virtual environment with a single source of truth. This virtual copy of an asset (or group of assets) is built at the same time as the physical asset to help organizations learn about their equipment and facilities and make the best use of them.

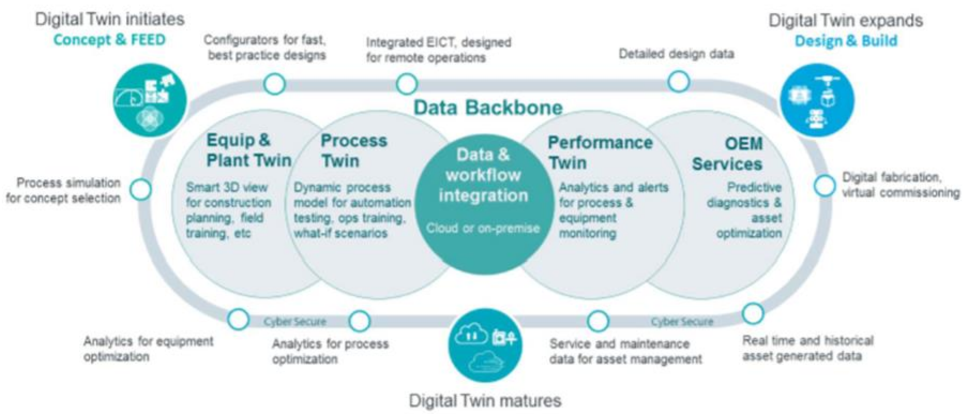

Figure 82. Components of the Intelligent Digital Twin structure. Society of Petroleum Engineers (LaGrange, 2019)

Refineries are characterized by the evolution of cumulative data. Over the project lifecycle, massive amounts of asset information are created. The issue that many operators have is that this data is distributed throughout a variety of software programs, platforms, and paper records throughout the organization and on-site. (Sircar et al., 2022) As a result, decision-makers frequently have false or incomplete, out-of-date, inconsistent, and/or poorly synced information.

This issue is addressed by integrating process engineering and plant engineering, physical layout modeling, asset performance modeling, maintenance modeling, and project and construction planning.

It also makes it possible and enabling to combination for controlling and evaluation of the information and data collective from different sources so that data isn't duplicated. The digital twin helps with the whole project lifecycle, starting with the client's concept development and ending with an as-is digital representation of the physical asset that gives operators valuable information about how well their asset works over its whole lifecycle. (LaGrange, 2019)

Also, the digital twin technology gives information about how the asset works, which can help with maintenance and figuring out when it needs to be fixed. This, in turn, can lead to reduced downtime and improved efficiency.

Adopting an integrated data backbone is a vital key part of making a digital twin work. Engineering and maintenance departments, subcontractors, vendors, and other stakeholders can all share the plant's as-built and as-maintained information data. Instead of giving and attempting to save hard copies of documentation, the many stakeholders give data records, which significantly simplifies and accelerates the process. This ensures comprehensive information clarity for every plant object and thus improves the work flow, reducing the risk of lost documentation and allowing for easier access to important information. Additionally, it promotes timely decision-making and more efficient communication among stakeholders.(LaGrange, 2019)

By implementing real-time plant monitoring systems, operators can receive accurate and current data. This can lead to improved safety and efficiency, as well as reduced downtime and maintenance costs.

Modeling, controlling, and optimizing petrochemical and refinery facilities is challenging. This is due to the plants' thousands of variables, including pressures, temperatures, flows, and product specifications, which must be continuously adjusted and calibrated by a team of operators and engineers on a 24/7 basis.

Numerous observed and unobserved disturbances, such as feedstock composition, weather, utilities, equipment, inventory levels, product prices, contracts, and many more, constantly alter these variables. The interdependence of the relationships between these variables is what causes the sheer complexity.

These erratic relationships frequently influence one another and cannot be separated from one another. Keep in mind that variables can linearly affect a variety of other variables. (Imubit, 2021) Nonlinearity develops, however, when relationships between some variables are impacted by other variables.

To maintain desired result number 1, one must go back and adjust variable number 1 if one sets variable number 1 to get desired result number 1 and then continues to set related variable number 2 to get desired result number 2.

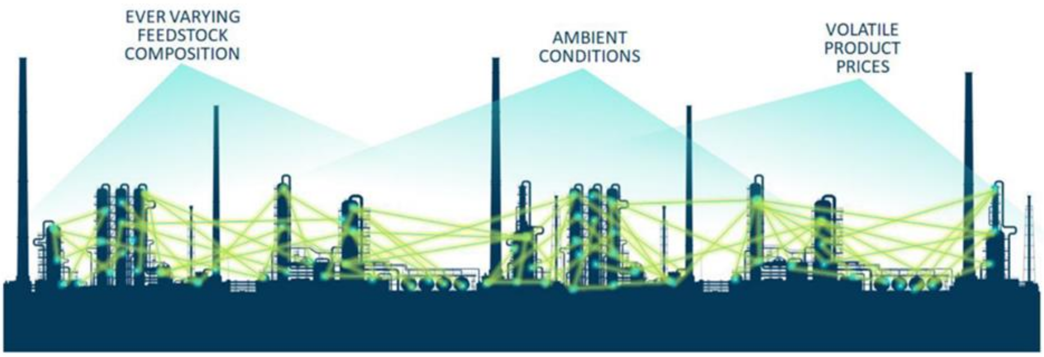

Figure 83. Plant is nonlinear: Relationships between variables cannot be isolated. They are interdependent on each other. AI in Refining .(Imubit, 2021)

This is due to the fact that changing variable No. 2 has altered the connection between variable No. 1 and result No. 1. This is what non-linearity is all about. It causes a long-standing issue in the hydrocarbon processing sector, which the aforementioned ongoing disturbances only serve to exacerbate. (Imubit, 2021)

The autonomous plant operation uses the latest developments in integration functions, connectivity functions and computing capabilities, including access to real time data and information from the Industrial Internet of Things (IIoT), to incrementally improve efficiency and performance using data analytics techniques, artificial intelligence (AI) tools , and first-principles models without a lot of human involvement. (Joly et al., 2018)

This technology can significantly increase efficiency by identifying and addressing issues before they become major problems. Additionally, the autonomous plant can lead to increased safety and cost savings for companies.

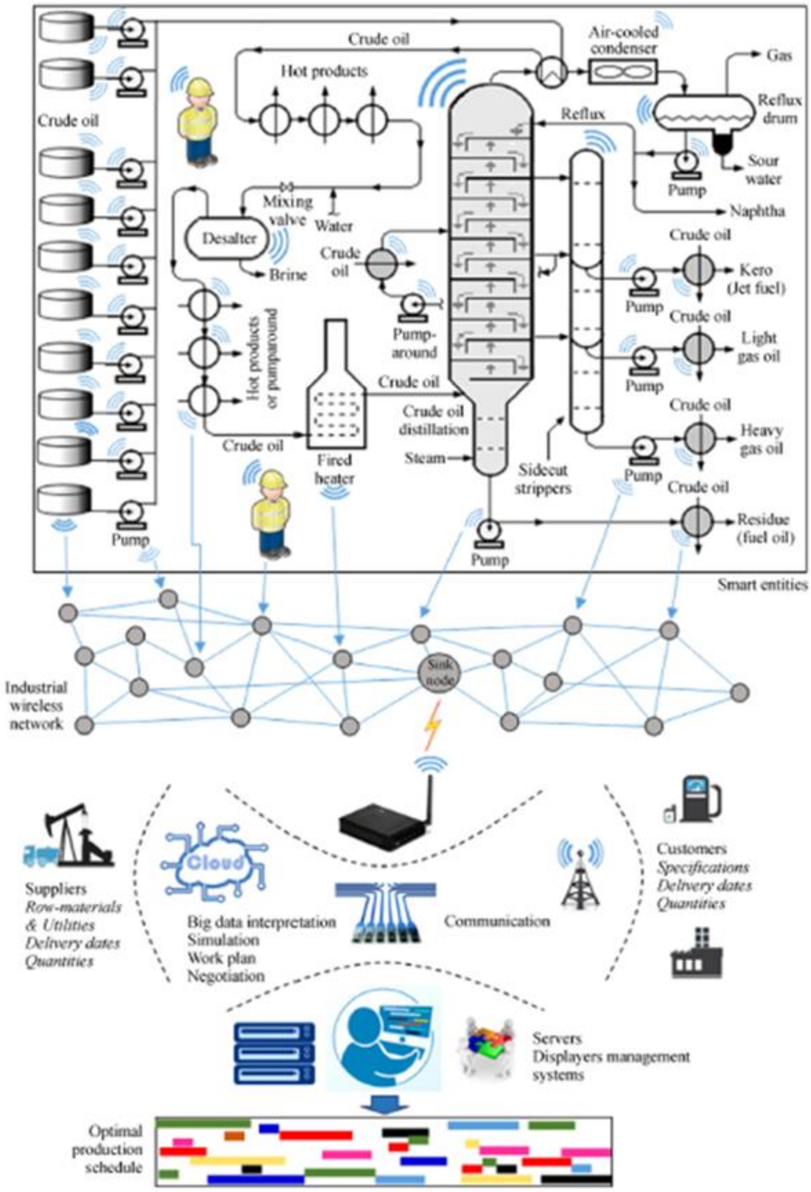

Figure 84. Conceptual model for an oil refinery running under a self-consciousness technological background. (Joly et al., 2018)

When making operational decisions about refineries or petrochemical plants, a carefully chosen mix of traditional technologies, AI, data that is always available, connectivity, and collaboration are used. (Joly et al., 2018)

The autonomous plant concept combines these elements to enable a more efficient and predictive operations management system with minimal human intervention. With the help of this system, plants can also optimize operational costs, reduce downtime, and ensure employee safety.

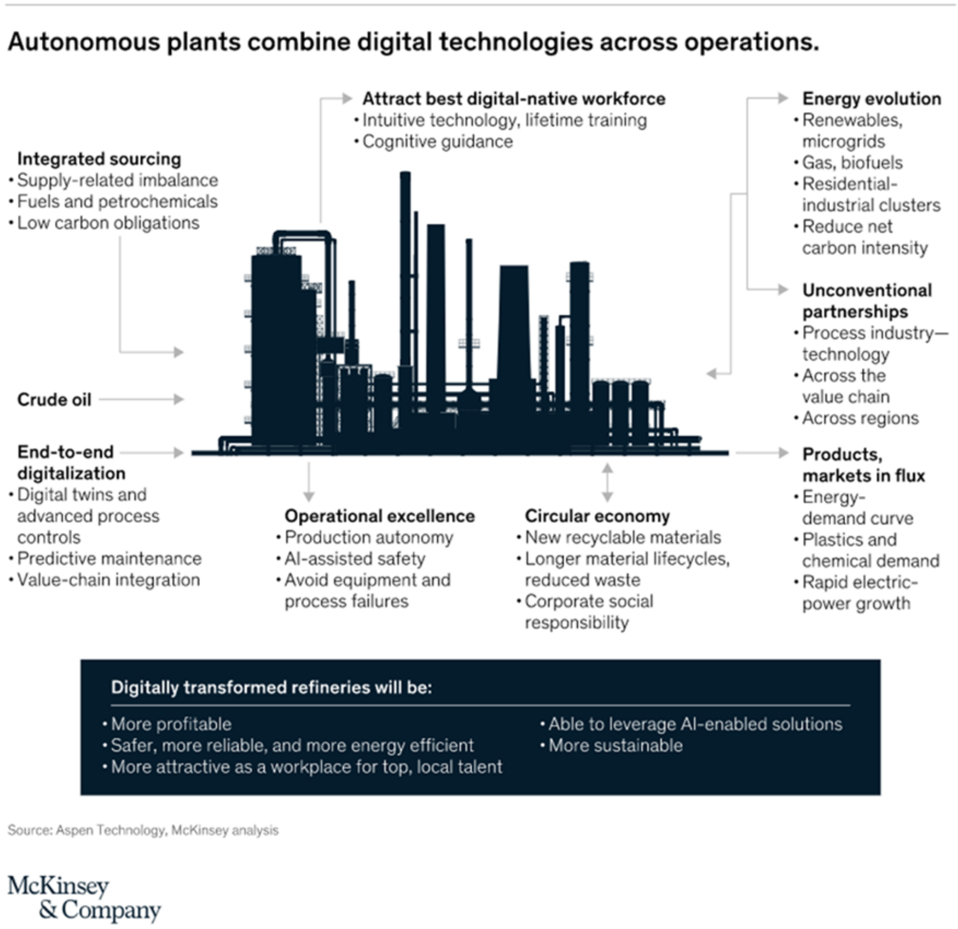

Figure 85. Autonomous Plant. McKinsey & Company (Chakrabarti et al., 2021)

When prescriptive analytics are used on operations feeding data and traditional models, they give to operators improved information and can show them other ways to do things, such as giving advice to operators or, in closed-loop systems, taking control automatically.

Increasingly autonomous technology may and can assure that businesses functions shall have a resilient and flexible asset that can be adjust and eligible to reorganized to grow in demandable environment with changing economic and operational factors inside a or demanding and volatile markets by merging technology and process with care and safety.

Many businesses buy and stays into the initial value proposition of technology and application platforms and software, but they don't use them to their maximum potential or continue to utilize them. Autonomous plants need a strategy for all operational and management tasks that is enabled by digital technology. (Chakrabarti et al., 2021)

Without maximizing the potential of technology platforms, businesses risk missing out on the benefits they offer in terms of operational and management efficiency. For autonomous plants, a digital strategy that covers all aspects of operation and management is essential for success in today's market.

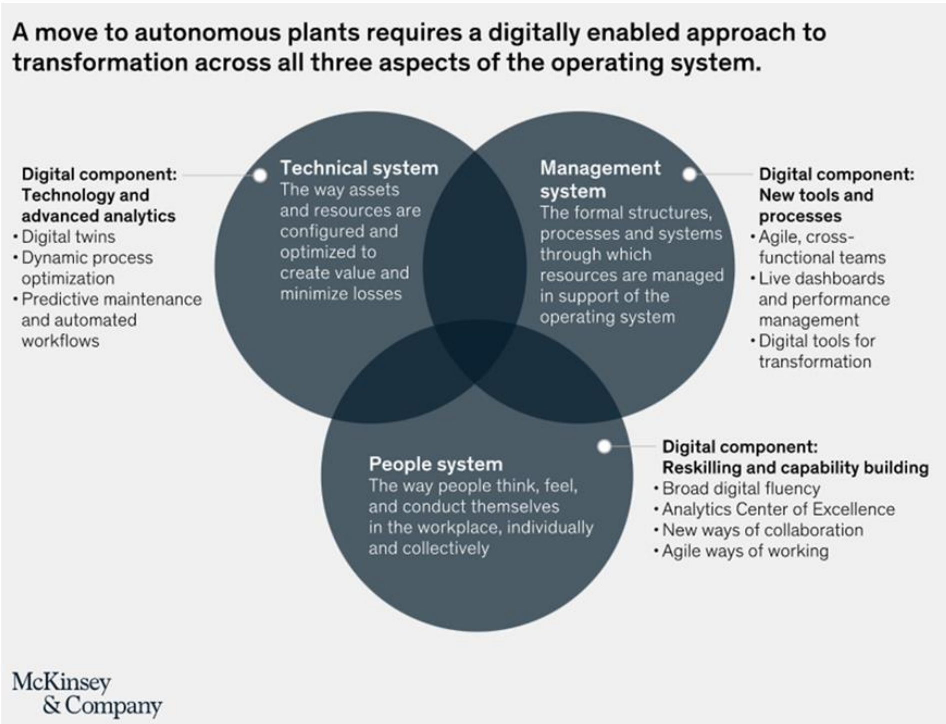

Figure 86. The full potential of autonomous technology. McKinsey & Company (Chakrabarti et al., 2021)

It makes sense for management to focus on the technical systems and investments that are needed to get started on the road to autonomy. This is because it is obvious what technical systems and investments are required. However, the heads of companies need to pay equal attention to how the new technology interacts with the management systems, behaviors, and skills that are already in place. Failure to consider the integration of new technology with existing management systems, behaviors, and skills could result in inefficient operations and decreased productivity. Therefore, it is crucial for company leaders to also focus on the cultural adaptation and training necessary for successful implementation.(Hou et al., 2020)

A new digital management approach, systems, and practices will be required in order to manage how personnel, technical or not, interact with the new systems, they will need to learn new ways to do their jobs. Existing hierarchical structures will be decomposed, and key value-driving tasks will be given to cross-functional teams. Lastly, recommendations for improving production will be made in a way that is dynamic and real-time. This will increase efficiency and improve product ratios while maintaining control and meeting sustainability targets. (Yokogawa, 2022)

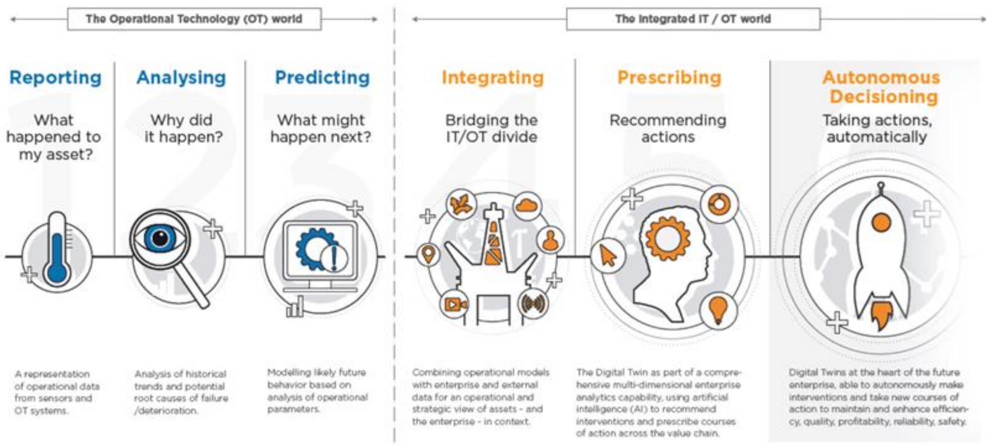

Figure 87. Stages and functions of a Digital Twin. (Nhede, 2018)

The implementation of automation technologies and data analytics tools can facilitate this real-time approach to production improvement. Such technologies can enable accurate tracking of production metrics and identification of bottlenecks, thus allowing for prompt remedial actions. Moreover, fostering a culture of continuous improvement and innovation can also help drive production efficiency, as employees become empowered to suggest and implement process improvements.

Operations and data-science teams must become multidisciplinary. Teams personnel from various departments learnt and qualified on transitioning from single-variable optimization (either optimizing for throughput or recovery) to multi-objective solutions for greater optimization. (Noterdaeme et al., 2018) Yet, adopting an agile approach may necessitate rethinking team roles. It is important for teams to be flexible and adaptable to changing needs, and reorganizing roles may be necessary to facilitate this.

Additionally, an agile approach may require a shift towards cross-functional collaboration and shared responsibility.(Trendminer, 2023)

Several facilities struggled to run at the lowest rate when demand was low. Several plants were unable to synchronize different restrictions and process units to meet production objectives and maintain safety without closed feedback loops because their planning and control systems were not optimized at low levels. (Chakrabarti et al., 2021; Pietri, 2020)

Under "normal operating conditions," these closed feedback and feedforward loops allow the facility to safely operate much nearest to its limitations as per operational principles. As result of inefficient planning and control systems, the plants experienced difficulties reaching production targets without compromising safety measures at low throughputs.

Closed feedback and feedforward loops can mitigate these issues and enable safe operation under normal circumstances.

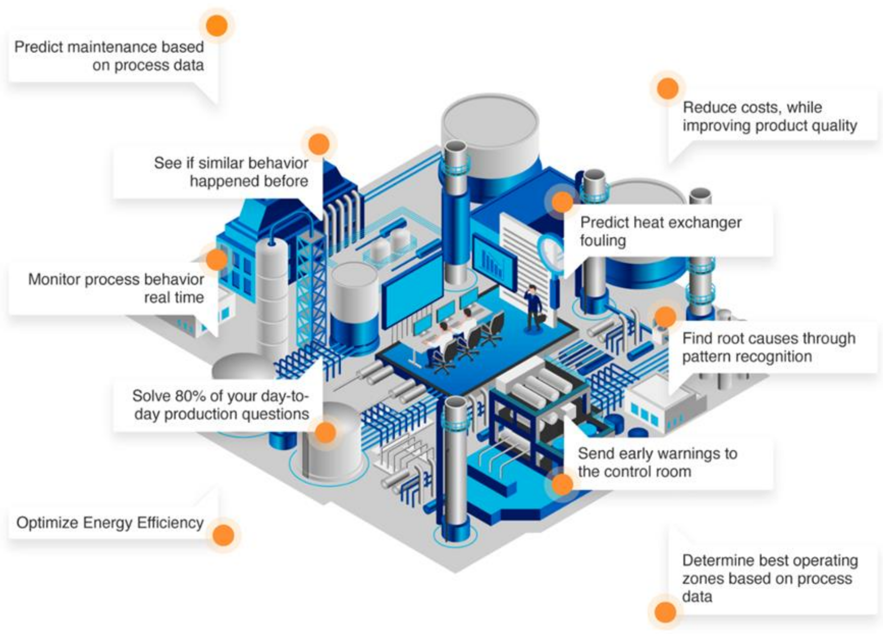

Figure 88. Self Service Analytics. Optimize production and manufacturing processes. (Trendminer, 2023)

Digital maturity can range from basic operations to autonomous business in petrochemical industry. This maturity model indicates how long it takes to deploy new technologies, implement new management approaches and processes, implement new workforce skills, and adopt different organizational and working behaviors.

Automation increases plant and corporate ecosystem value. The maturity model allows organizations to assess their ability to embrace changes in technology and management practices. With automation, companies can increase their overall value and efficiency across their operations.

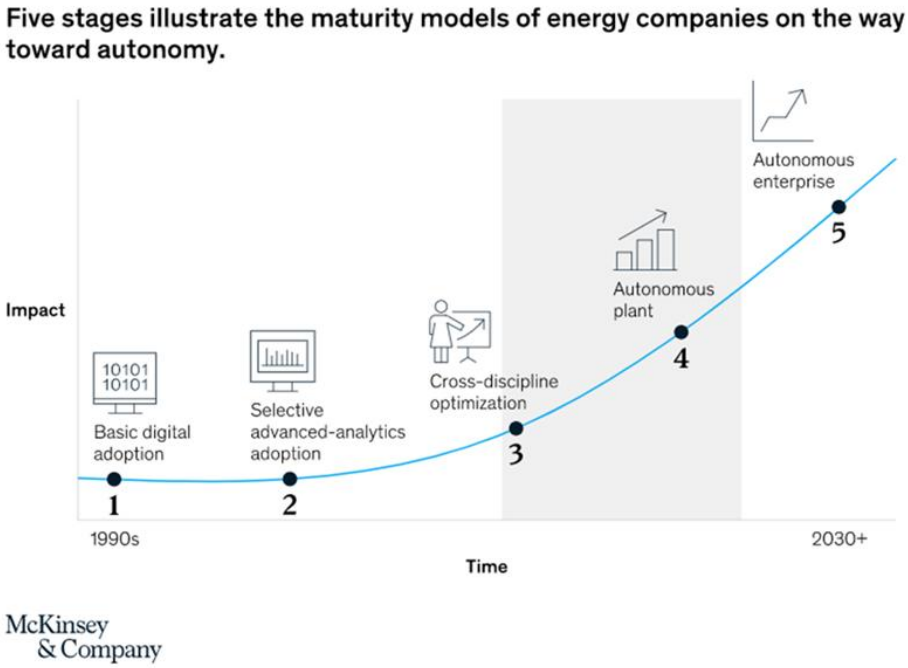

Figure 89. Maturity model towards digital autonomy. McKinsey & Company (Chakrabarti et al., 2021)

There is a large variety of maturity level, from simple operational control systems at factories to organizations that are completely integrated and operate on their own. The way digitalization is used changes with each stage following the initial one. As a result, businesses need to consider the maturity level of their infrastructure to determine their digitalization needs. In order to fully leverage the benefits of digitalization, organizations should strive for greater integration and automation of processes.(Chakrabarti et al., 2021)

Basic digital adoption

Most organizations are now operating at this level of maturity, which is characterized by the most basic use of control systems in operations, site-by-site elementary refinery planning, spreadsheet-based scheduling, ad hoc troubleshooting-induced process modeling, and maintenance functions with work orders. Businesses at this level in their digital transformation typically lack anything resembling a digital organization and regard updating their present systems to reflect best practices and instituting business-process collaboration as the next steps in their digital journey. As these organizations strive to keep up with changing consumer demands, they are realizing the need for more sophisticated digital technologies to enhance their operational efficiency and decision-making capabilities. Moving beyond the basic use of control systems and ad hoc troubleshooting will require significant investments in digitization and a shift in organizational culture towards embracing disruptive innovation. (Chakrabarti et al., 2021)

Selective advanced-analytics adoption

In the last years, some businesses have taken the first step toward this next stage by implementing limited APC use, advanced techniques and tools in linear programming modeling methodologies, and Enterprise Resource Planning (ERP) software. Nowadays most forward-thinking businesses apply advanced analytics tools for value-creating using tools and functions including data analytics, based preventative maintenance for availability, adaptive advanced process control, and online optimization of small entities. (Chakrabarti et al., 2021)

Besides these positive developments, it is still in the responsibility of each leader to promote the implementation of digital solutions through pilot programs rather than a complete cultural acceptance of disruptive technologies. Moreover, many organizations have not invested in creating a robust edge-to-enterprise sensor and data strategy.

Cross-discipline optimization.

At this point, businesses are actively experimenting with cross-discipline optimization, deploying and integrating a wide range of digital solutions. Most of these businesses have already learned to scale, so they have a good idea of where digital deployments will yield the most returns.

Such examples include businesses with enterprise-wide ERP systems, multi-unit process improvements, and asset-wide digital twins applications for monitoring, as well as those with completely integrated planning and scheduling solutions. They also have the beginnings of digital organizations and a growing sense of cultural enthusiasm for the potential of technological solutions.

Figure 90. Traditional process control and optimization hierarchy. (Imubit, 2021)

If the right solutions are implemented and the business provide a good and positive outcome, digital projects can become "self-funding" and adoption barriers can be lowered dramatically. Because this is such a pivotal milestone, rapid adoption is essential right now if we're going to be ready for the next level of development down the road.

Autonomous plant.

To reach this stage, you must trust digital technologies more, align your business functions, and create completely organizations in digital form that promote constant transformation. By that organizations should consider closed-loop process functions, optimization, integrate and embed site workflows functions, and as result the positive outcome meaning to save costs due to reduced labor, more stable processes, and higher reliability. (Chakrabarti et al., 2021)Front-line personnel help technical support professionals implement the digital plan.

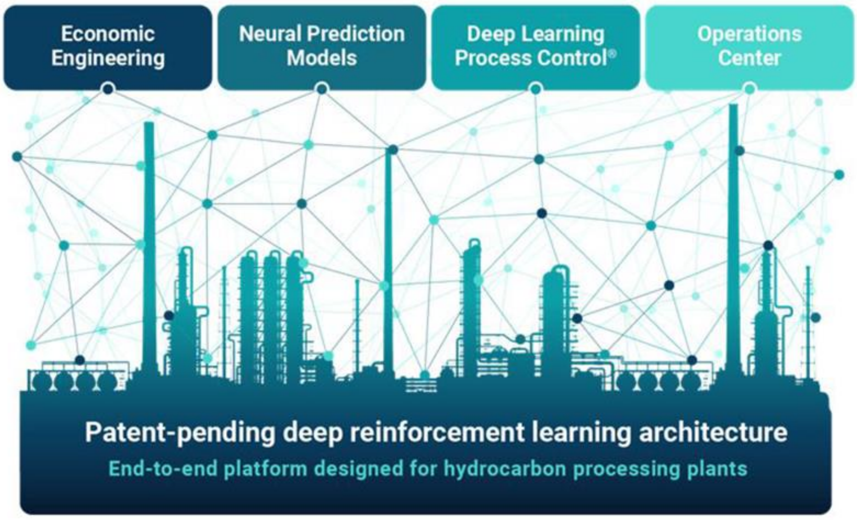

Figure 91. Imubit Closed Loop Neural Network Platform. (Imubit, 2021)

Many locations are implementing integrated systems to enable autonomous plants, even though none exist yet. AI-enabled hybrid solutions are essential now.

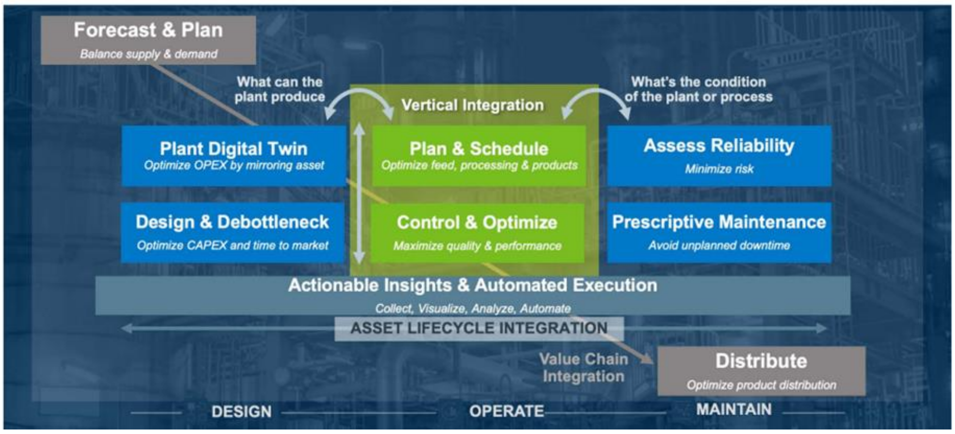

Figure 92. A Vision of smart refining. Aspen Tech (Hou et al., 2020)

These integrated systems will allow for improved monitoring and control of plant operations, leading to increased efficiency and productivity. The use of AI and automation will also reduce costs and minimize the risk of human error.

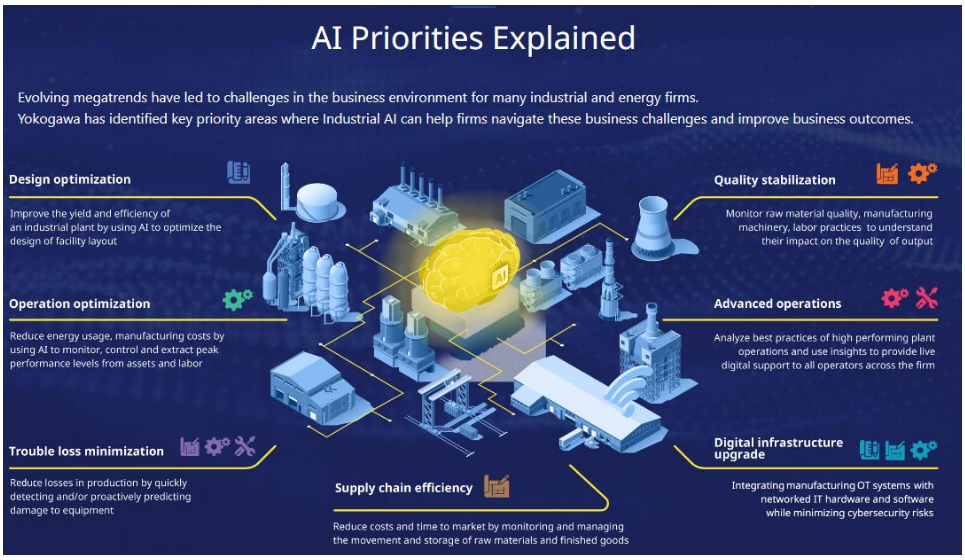

Figure 93. Industrial AI, Building Next-Gen Autonomous Operations. (Yokogawa, 2022)

Autonomous enterprise.

The enterprise value chain is the only thing that gives plants and assets a purpose. To get the most out of an autonomous plant, the whole value chain needs to be smart as well. So, it can decide across the whole business network which assets make which products and which goals are being met for each specific product and manufacturing line at each site. This is the ultimate example of independence, as the name suggests.

Currently, there is full solution integration, visualizations of data in real-time monitoring and captured data providing continuous optimization actions across plants, and site-level workflows are linked to equally sophisticated back-office workflows. Even though no business can be called "autonomous" right now, many are researching and developing different parts of this new field. (Chakrabarti et al., 2021) As technology advances, it's possible that more businesses will become fully autonomous. However, there are still many challenges that need to be addressed, such as safety concerns and ethical considerations. To achieve true autonomy, businesses will need to combine advanced Artificial Intelligence and Machine Learning capabilities to enable independent decision making. However, this will require a significant investment and expertise. (Yokogawa, 2022)

When you think about the digital maturity model, the most important thing to remember is that every organization, no matter where it is on the path to autonomy or how far it has come, has steps it can take. All plants and businesses can use digitalization to move forward and keep changing their cost bases. With ongoing digitalization throughout the industrial factories and enterprises, may increase their operation with more self-sufficient way having the ability for self-optimizing, which laying the groundwork for an autonomous enterprise.

CHAPTER 5

Conclusions

The use of digital twin applications, is simplifying not just the production and manufacturing activities and processes but also our everyday lives. The digital twin is a connection that may be found across the whole manufacturing process. It incorporates digital models and shadows. The combination of various digitalization strategies leads to an improvement in output as well as an increased ability to monitor it all along the manufacturing process. This results in a shorter amount of time needed for manufacturing, a less amount of waste created, and ultimately a greater amount of money made, meaning bigger revenues for the enterprises. The digital twin provides enterprises with a more efficient and cost-effective way of creating, monitoring, and optimizing their products throughout the manufacturing process. Therefore, the use of the digital twin has become increasingly popular for companies that want to stay competitive and to maintain their positions as market leaders worldwide.

In the past few years, there has been a rise in interest in DT because it is a new, practical technology that allows real and virtual places to blend together in a seamless way. The development of the DT from its start in 2003 until now is looked at, and its many theoretical foundations, as thought of by both academics and business people, are talked about. According on this information, the basic parts of the Digital Twin are the model, exchanged data and connections, and finally services, which all are crucial and with essential tasks within the operation of a Digital Twin. Companies can take advantage of this technology to better manage and maintain their operations, especially if they want to remain competitive in the international marketplace.

At the moment, a wide range of industrial sectors are using these digitalized ideas and concepts.

Digital models are amazing for use in industrial design, the creation of innovative concepts and products Digital shadows may be useful for monitoring production. Companies that use this technology will be enabled to improve production and make more intelligent choices concerning their operations, increasing efficiency, and remain competitive in the global market. A digital twin is an effective application which analyzing and evaluating data in how real-time manufacturing works.

So, if businesses choose a platform that has these features, they may be able to use a strong digital transformation tool for data-driven analysis. Intelligent platforms for digital twins that are built on objects can make digital twins that look real by using 3D models to capture digital shadows. When digital twins are complete, they can be used to analyze manufacturing processes and make decisions from a distance. They can also be used to keep an eye on things from a distance. These digital twins are then able to become a data-driven tool for companies to gain insight into their manufacturing processes.

It is feasible to optimize procedures and redefine product development due to the deep insight afforded by the technology known as digital twins," which applies to both the assets and the manufacturing processes involved. Taking under consideration the significant uses of the digital twin application, model, and shadow in a variety of different industrial or business sectors.

Businesses can immediately determine if anything is wrong or not working properly after conducting a thorough examination of how well and healthy the equipment is.

Shutdowns and expensive asset failures can be avoided by planning preventative maintenance and restocking replacement parts ahead of time.

This can be done using a scheduling system. For manufacturers, one of the significant gains of predictive maintenance is increased product reliability. Another benefit is the creation of new revenue streams through service-based business strategies. Predictive maintenance can help industrial companies reduce asset downtime, generate new business opportunities, and offer higher-quality products with fewer failures Additionally, by leveraging predictive maintenance, manufacturers can reduce operational and inventory costs by using just-in-time part replenishment.

With the use of virtual prototypes, one may get an in-depth look into the usage patterns of a product, as well as its point of deterioration, its workload capacity, and the incidence of faults. By learning more about how the product works and what causes it to fail, it is possible to make parts with better designs. The adaptation of the digital twin makes it easier to build virtual prototypes and test features using real-world data. This is one of the many advantages of technology. With the use of the application of the digital twin, companies are able to identify potential design flaws and improve parts designs in real-time with the minimum cost.

Lastly, a digital footprint that combines information from sensors and ERP systems on a production line could be used to look at key performance indicators (KPIs) like production rates and scrap counts to plan and improve the manufacturing process. This drive to perform root cause analysis studies of any inefficiencies, which helps to improve productivity and get rid of waste in the production process. Taking this a step further, data about equipment, processes, and surroundings can be used to calculate unavailability, which helps improve production planning. In addition, technological advancements have allowed organisations to handle and utilize with more appropriate way data and information in order to optimize their production and manufacturing processes.

Future works

A fully autonomous plant or refinery is the optimum solution, based on advanced algorithms of artificial intelligence data systems that will be self-learning, for the operation of the refinery across the production cycle, from the input of feedstock to the output of the final and finished goods to the market, including production operation, storage, and maintenance, and after that, the whole supply chain of the enterprise.

The human factor will finally be limited only to supervisory roles and emergency operations, if any arise. We have to consider the minor possibility that even the most technologically advanced systems sometimes fail.

However, the increasing reliance and addiction on technology trends also raises concerns about cybersecurity threats and the need for continuous monitoring and updates to ensure system reliability. Additionally, it is important to support and preserving a balance between automation implement and human involvement to avoid complete dependence on technology.

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