619130-EPP-1-2020-1-FR-EPPKA2-CBHE-JP

Selection: 2020

KA2 – Cooperation for innovation and the exchange of good practices –
Capacity Building in the field of Higher Education

strENgtHening skills and training expertise for TunisiAN and MorocCan transition to industry 4.0 Era / ENHANCE

D1.1. Literature review about required skills related to MPQ4.0

Deliverable Identifier	**D1.1**
Deliverable Date	**M6 – 30/06/2021**
Deliverable Version	**V 1.4 – 2022**
Deliverable Leader	**BIBA**
Deliverable participants	**All**
Dissemination Level	**Public**

Document Control Page

Title	Literature review about required skills related to MPQ4.0
Version	V1.4 – 2022
Deliverable number	D1.1
Work-Package	WP1
Status	☐ Draft ☐ Under Review ☐ Under Update ☐ Accepted by the coordinator ☒ Submitted to the commission
Authors	Zied Ghrairi
Contributors	All partners
Peer Reviewers 1:	Joao Sousa
Assigned Date	31.05.2021
Received Date	11.06.2021
Peer Reviewers 2:	Saber Darmoul
Assigned Date	15.06.2021
Received Date	18.06.2021
Date of Delivery	30.06.2021
Dissemination level	☒ Public ☐ Confidential, only for ENHANCE Consortium (including EC) ☐ EU-Restricted

Version History

Version	Date	Description	Edited by
1.0		Initial Version	BIBA, ECC, UCAR, ULL
1.1	30.05.2021	Draft for Consortium sharing	BIBA, ECC, UCAR, ULL
1.2.1	14.06.2021	Final Draft with integration of comments from reviewer1	BIBA
1.2.2	29.06.2021	Final Draft with integration of comments from reviewer2	BIBA
1.3	31.06.2021	Final Version	BIBA
1.4	14.09.2022	Submitted to the commission	ULL

Executive Summary

Industry 4.0 has brought a set of new technologies and practices that are disrupting traditional ways of work and value creation. In an industry 4.0 era, companies are facing complex challenges due to technology advancements, demand variability and mass customization. To meet these challenges, companies need to improve the effectiveness and efficiency of their assets, to upgrade their business processes to the latest technologies and best practices, and subsequently, to lead digitization and transformation projects. Therefore, companies need to rely on qualified workforce, already trained on required skills and practices to deploy and use industry 4.0 technologies and practices effectively and efficiently. The challenge is how to update Higher Education curricula to be able to provide such up-to-date training to their learners. Performing a requirements study of skills for Maintenance, Production and Quality (MPQ) in the era of Industry 4.0 is of significance because it informs employment seekers and skill development institutions about what to work towards and what to expect. Technological megatrends will significantly affect the skills and competencies needed, thus requiring organizations to develop strategies, and skill development institutions to be innovative, in creating the required skills and competencies. This document is developed as part of the ENHANCE project to explain the state of the art about the required skills related to MPQ4.0. The findings of this work is to provide a supportive guideline for HEIs in Partner Countries (PC) to acquire new MPQ4.0 training expertise (by faculty members) and skills (by students, researchers, and industrial staff) for supporting local industries in the appropriation of the MPQ4.0 concepts and solutions.

The document highlights the nine pillars, enabling technologies, of Industry 4.0 and the SoA reference architectures. In addition, it explains the European, Tunisian and Moroccan strategic plan and roadmaps. The work describes the implementation of these technologies in the predefined and new identified concepts for the topics maintenance, production and quality 4.0. Numerous related practices and finished/ongoing R&D projects are introduced. Finally, the document provides an abstraction framework based on competencies, skills, and abilities for a successful industry 4.0 transition.

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List of acronyms

AI	Artificial Intelligence
AM	Additive Manufacturing
ANNs	Artificial Neural Networks
APII	Tunisian Agency for the Promotion of Industry and Innovation
AR	Autoregressive Filtering
ASQ	American Society for Quality
B2C	Business to Consumer
BCG	Boston Consulting Group
BD	Big Data
BDA	Big Data Analytics
CAD	Computer-Aided Design
CAQ	Computer Aided Quality
CBM	Condition Based Monitoring
CE	Circular Economy
CFD	Computational Fluid Dynamics
CMg	Cloud Manufacturing
CMMS	Computerised Maintenance Management System
CNN	Convolutional Neural Networks
CPPS	Cyber Physical Production Systems
CPS	Cyber Physical Systems
DCS	Distributed Control System
DGQ	Deutsche Gesellschaft für Qualität
DIH	Digital Innovation Hub
DIK	Data, Information, and Knowledge
DL	Deep Learning
DSS	Decision Support System
DT	Digital Twin
PPC	Production Planning and Control
EFFRA	European Factories of the Future Association
EFQM	European Foundation for Quality Management
ETP	European Technology Platforms
GDSS	Group Decision Support Systems
HEI	Higher Education Institutions
HRC	Human-Robot Collaboration
ICT	Information Communication Technology
IIoT	Industrial Internet of Things
IIRA	Industrial Internet Reference Architecture
IoT	Internet of Things
ISO	International Standardization for Organization
IT	Information Technology
ITCEQ	Tunisian Institute for Competitiveness and Quantitative Studies
IVRA	Industrial Value Chain Reference Architecture
KBS	Knowledge-Based Systems
KNN	K-Nearest Neighbor
LASFA	LAsim Smart FActory
LTA	LifeTime Assessment

LTE	LifeTime Extension
MES	Manufacturing Execution System
ML	Machine Learning
MPQ	Maintenance Production Quality
MPS	Master Production Scheduling
MRP	Material Requirements Planning
NF	Neural Fuzzy
PC	Partner Countries
PEID	Product Embedded Intelligent Devices
PPP	Public-Private Partnership
RAMI 4.0	Reference Architectural Model Industrie 4.0
RTQCIS	Real-Time Quality Control Information System
RUL	Remaining Useful Life
RVK	Relevance Vector Machine
S&OP	Sale and Operations
SD	Sustainable Development
SITAM	Stuttgart IT-Architecture for Manufacturing
SME	Small and Medium Enterprises
SOP	Standard Operating Procedures
SoSM	Service-oriented Smart Network
SVM	Support Vector Machine
TQM	Total Quality Management
VR	Virtual Reality
WEEE	Waste Electrical and Electronic Equipment
XR	Virtual, Augmented and Extended/Mixed Reality

1. ENHANCE: project overview

ENHANCE – strENgtHening skills and training expertise for TunisiAN and MorocCan transition to industry 4.0 Era – is an Erasmus Plus project founded under the KA2 Cooperation for innovation and the exchange of good practices (Capacity Building in the field of Higher Education) programme by the European Commission under Grant Agreement N° 619130, to be conducted in the period January 2021 until January 2024. It engages 7 partners from 5 countries with a total budget of 779k€. Further information can be found at http://eplus-enhance.eu/.

The emergence of industry 4.0 concepts and applications brings new paradigms impacting all the industrial business domains when they need to conduct successful digital transformations or increase workshops connectivity. The evolution of Maintenance, Production and Quality Engineering (MPQ 4.0) represents the main application domains where Industry 4.0 produces effective beneficial results.

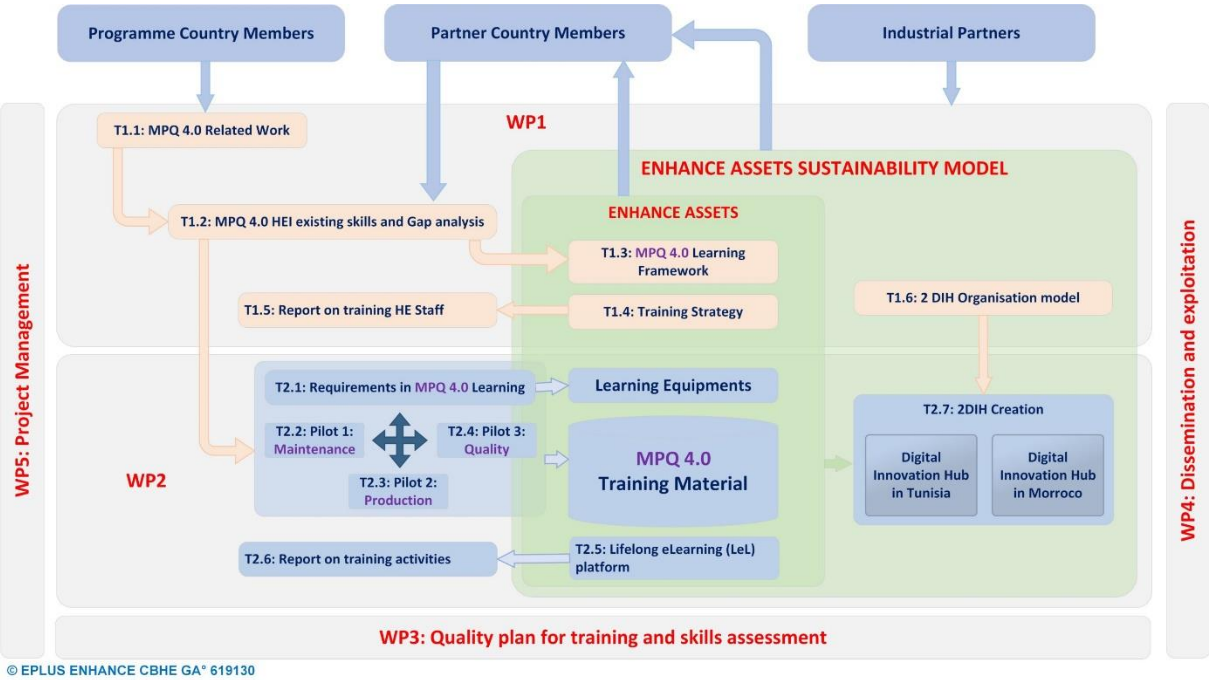

Figure 1. ENHANCE project organization.

The ENHANCE project focuses on building new MPQ training capacities at Higher Education Institutions (HEI) in Tunisia and Morocco to establish interactions between the following stakeholders:

- European universities and research institutions (from France, Germany and Portugal) confirmed MPQ 4.0 competencies, training materials, collaborative research projects, full operational Digital Innovation Hubs (DIH), technology transfer experiences, etc.
- Partner country universities (from Tunisia and Morocco) with teaching and training activities in MPQ and existing connections with their local industrial partners.

The ENHANCE project will create several outputs and two primary tangible outcomes:

- New MPQ 4.0 equipment and training materials developed in connection with the existing training programmes and consolidated through three industrial pilots. The new material will be used to train the trainers and the students in the different partner country universities.
- Two DIHs, one in Tunisia and one in Morocco to sustain the project outcomes through their reuse for training in industry.

ENHANCE aims to become the reference model for creating effective and sustainable training material for MPQ 4.0 in both partner countries with content approved by academia and industry.

2. Introduction

Industry 4.0 has brought a set of new technologies and practices that are disrupting traditional ways of work and value creation. In an industry 4.0 era, companies are facing complex challenges due to technology advancements, demand variability and mass customization. To meet these challenges, companies need to improve the effectiveness and efficiency of their assets, to upgrade their business processes to the latest technologies and best practices, and subsequently, to lead digitization and transformation projects. Therefore, companies need to rely on qualified workforce, already trained on required skills and practices to deploy and use industry 4.0 technologies and practices effectively and efficiently. The challenge is how to update Higher Education curricula to be able to provide such up-to-date training to their learners. Performing a requirements study of skills for Maintenance, Production and Quality (MPQ) in the era of Industry 4.0 is of significance because it informs employment seekers and skill development institutions about what to work towards and what to expect. Technological megatrends will significantly affect the skills and competencies needed, thus requiring organizations to develop strategies, and skill development institutions to be innovative, in creating the required skills and competencies.

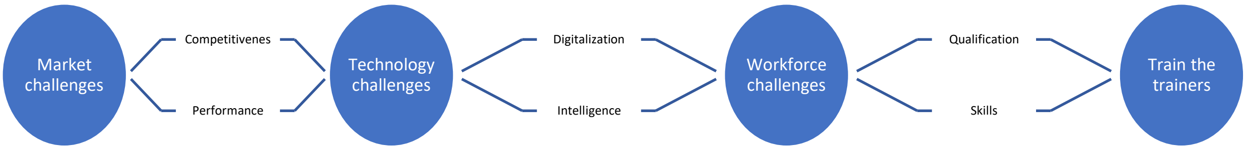

Figure 2. challenges requiring new industry 4.0 skills.

2.1. Purpose of the document

This document is developed as part of the ENHANCE project to explain the state of the art about the required skills related to MPQ4.0. It is expected that the findings of this work provide a supportive guideline for HEIs in Partner Countries (PC) to acquire new MPQ4.0 training expertise (by faculty members) and skills (by students, researchers, and industrial staff) for supporting local industries in the appropriation of the MPQ4.0 concepts and solutions.

2.2. Reference documents

N/A

2.3. Applicability

This document provides a comprehensive literature review about Industry 4.0-based concepts, used technologies and related competencies and skills needed in HEI and industrial companies. A particular focus will be given to skills related to MPQ4.0. The deliverable will support the process of gap analysis assessment in WP1.

2.4. Definitions

In the following, the main concepts used in this document are briefly explained:

- *Industry 4.0* – is the ongoing automation of traditional manufacturing and industrial practices, using data exchange and modern smart technologies (e.g., Internet of Thing (IoT), cloud computing, Cyber-Physical Systems (CPS), and cognitive computing) to improve companies' operation, products, and services
- *Skill* – encompasses the knowledge, competencies, and learned ability to perform an activity or job well with determined results
- *Training* – refers to the teaching, learning, developing knowledge, skills, or fitness that are needed to do a particular job or activity

- *Competence/Competency* – is the capability to use or apply a set of demonstrable characteristics, knowledge, skills, and abilities required to do a task effectively
- *Capability* – is the ability to do something or achieve certain actions or outcomes
- *Capacity* – describes the amount or number that somebody can hold, receive, or absorb
- *Knowledge* – refers to understanding and awareness of or familiarity with various objects, events, ideas, or ways of doing things that has been obtained by experience or study.[1]

2.5. Structure of the document

- Section 3 introduces industry 4.0 enabling technologies as well as strategic plan and roadmaps in partner countries to achieve industry 4.0 transition
- Section 4 describes implementations of industry 4.0 technologies and projects in Maintenance, Production and Quality Engineering fields
- Section 5 builds on top of section 4 to abstract skills required for a successful industry 4.0 transition.

[1] https://www.indeed.com/career-advice/career-development/knowledge-skills-and-abilities

3. Industry 4.0 paradigm, strategic plans and roadmaps

Industry 4.0 is a term often used to refer to the developmental process in the production of goods and/or services. The term also refers to the fourth industrial revolution. It was first publicly introduced in 2011 by a group of representatives from different fields (such as business, politics, and academia) under an initiative to enhance the German competitiveness in the manufacturing industry. The German federal government adopted the idea in its High-Tech Strategy for 2020 [1].

The fourth industrial revolution takes the automation of manufacturing processes to a new level by introducing customized and flexible production technologies. Production resources (machines, products, logistics, etc.) are enabled to operate independently, or cooperate with humans in creating a customer-oriented production field that constantly works on maintaining itself. Production resources rather become independent entities, able to collect data, analyse it, and advise upon it. This becomes possible by introducing self-optimization, self-cognition, and self-customization into the industry. The manufacturers will be able to communicate, cooperate and collaborate with computers rather than just operating them.

3.1. Industry 4.0 enabling technologies

In the literature, several authors discussed industry 4.0 enabling technologies [2–5]. These are synthesized in Table 1 and then briefly introduced in the following subsections.

Table 1. Summary of Industry 4.0 enabling technologies according to [4].

Technology	Description
Cyber-physical systems	CPS is a collection of transformative technologies that connects the operations of physical assets and computational capabilities. The main aim is to monitor physical systems while creating a virtual copy
Internet of things	Information network of physical objects (sensors, machines, cars, buildings, and other items) that enables the collection and exchange of data, allowing interaction and cooperation of these objects
Big data and analytics	Collection and analysis of large amount of available data using a series of techniques to filter, capture and report insights, where data are processed in higher volumes, with higher velocities and in greater variety
Cloud technology	System for the provision of online storage services for all applications, programmes and data in a virtual server, without requiring any installation
Artificial intelligence	System that think humanly and rationally according to six main disciplines, including natural language processing, knowledge representation, automated reasoning, machine learning, computer vision and robotics
Blockchain	A database that creates a distributed and tamperproof digital ledger of transactions, including timestamps of blocks maintained by every participating node
Simulation and modelling	Technologies that mirror the physical world data such as machines, products and humans in a virtual world, aiming for simplification and affordability of the design, creation, testing and live operation of the systems
Visualization technology (augmented and virtual reality)	Augmented Reality: a set of innovative Human Computer Interaction (HCI) techniques that can embed virtual objects to coexist and interact in the real environment; Virtual Reality: application of computer technology to create an interactive world, allowing the user to control the virtual object and whole virtual scene in real time
Automation and industrial robots	Machinery and equipment that automate operational processes, containing also Collaborative Robotics, which allows humans and machines to operate in a shared learning environment
Additive manufacturing	Process of joining materials in successive layers to make objects from 3D model data to ‘unlock’ design options and achieve great potential for mass-customisation

3.1.1 Cyber-Physical Systems (CPS)

Cyber Physical Systems (CPS) are integrations of computing and physical processes which are essential components of Industry 4.0 implementations [5]. In CPS, physical and software components are deeply intertwined, able to operate on different spatial and temporal scales, exhibit multiple and distinct behavioural modalities, and interact with each other in ways that change with context. CPS involve transdisciplinary approaches, merging theory of cybernetics, mechatronics, design and process science. The process control is often referred to as embedded systems. In embedded systems, the emphasis tends to be more on the computational elements, and less on an intense link between the computational and physical elements. CPS are also similar to the Internet of Things (IoT), sharing the same basic architecture; nevertheless, CPS present a higher combination and coordination between physical and computational elements. Examples of CPS include smart grid, autonomous automobile systems, medical monitoring, industrial control systems, robotics systems, and automatic pilot avionics. Precursors of cyber-physical systems can be found in areas as diverse as aerospace, automotive, chemical processes, civil infrastructure, energy, healthcare, manufacturing, transportation, entertainment, and consumer appliances. [6] define the 5C architecture for the realization of cyber-physical systems (CPS) with the levels smart connection (I), data-to-information conversion (II), cyber (III), cognition (IV), and configuration (V). The architecture serves as a guideline for implementations and realizations of CPS. Since then, several other Industry 4.0 reference architectures were suggested (see Section 3.1.11).

3.1.2 Industrial Internet of Things (IIoT)

The Internet of things (IoT) [5] describes the network of physical objects, also referred to as "things", that are embedded with sensors, software, and other technologies for the purpose of connecting and exchanging data with other devices and systems over the Internet. Things have evolved due to the convergence of multiple technologies, real-time analytics, machine learning, ubiquitous computing, commodity sensors, and embedded systems. Traditional fields of embedded systems, wireless sensor networks, control systems, automation (including home and building automation), and others all contribute to enabling the Internet of things.

The Industrial Internet of Things (IIoT) [7] refers to interconnected sensors, instruments, and other devices networked together with computers' industrial applications, including manufacturing and energy management. This connectivity allows for data collection, exchange, and analysis, potentially facilitating improvements in productivity and efficiency as well as other economic benefits. The IIoT is an evolution of a distributed control system (DCS) that allows for a higher degree of automation by using cloud computing to refine and optimize the process controls.

3.1.3 Big Data Analytics (BDA)

The interconnection of heterogeneous objects leads to the generation of huge amounts of data from different sources, of different types, and with different sizes and frequencies. These structured, semi-structured and unstructured data are referred to as Big Data (BD). If processed traditionally, such data would need too much time and money to be stored and to be analysed. Bringing value opportunities to industries in the era of Internet of Everything can be achieved with the connection of more physical devices to the internet and with the use of a generation of novel technologies. Data collection or storage characterize BD, but the core characteristic of BD is the data analysis and without it, BD has no much value. Systematic guidance can be provided by BD for related production activities within entire product life cycle, achieving cost-efficient running of the process and fault-free, and help managers on decision-making and/or to solve problems related to operation. The use of BD provides a business advantage through the opportunity of generated of value-added. Various stages in data lifecycle where manufacturing data is exploited are depicted in Figure 3 consisting in the complete manufacturing data journey. BDA is an essential key to digital manufacturing, playing as an enabler for technologies. Moreover, the scope of mass customization focusing on the needs of individualized markets, use BD analytics as foundation.

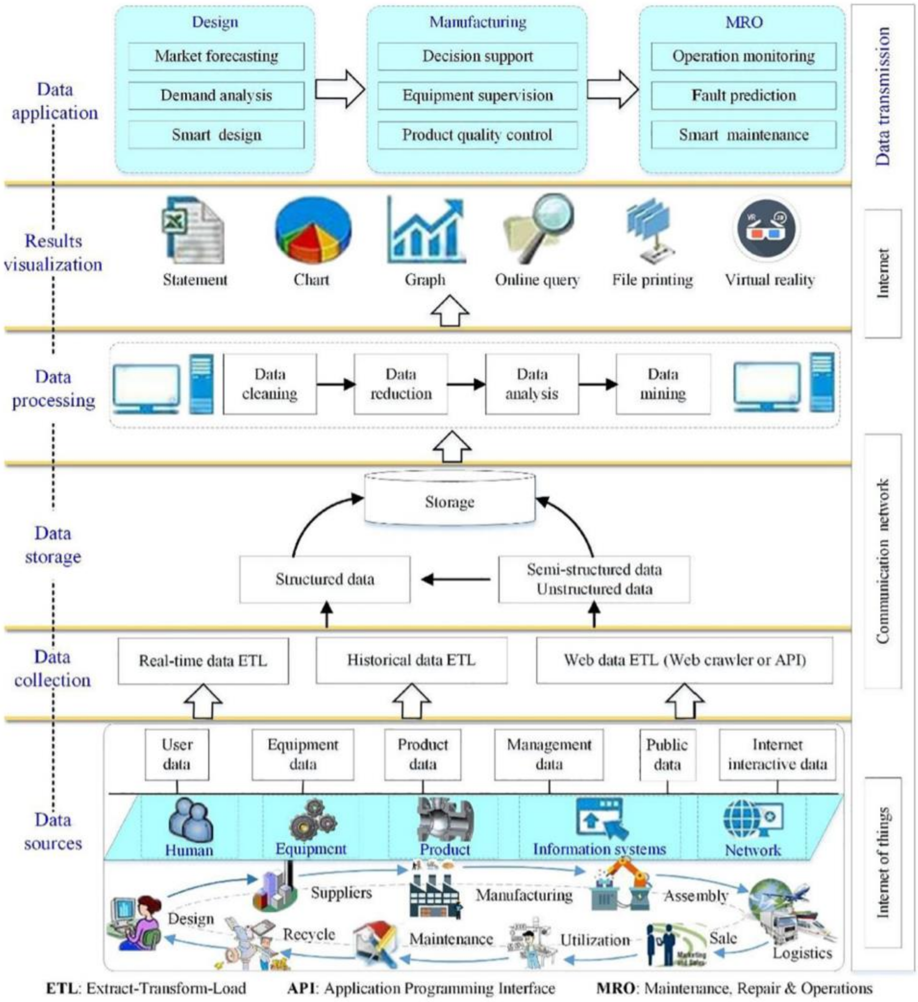

Figure 3: Manufacturing data lifecycle [8]

3.1.4 Simulation/Emulation

Computer simulation is becoming a technology to better understand the dynamics of business systems. Manufacturing industry current challenges can be approached by this technology, dealing with the complexity of the systems, with elements of uncertain problems that cannot be resolved with usual mathematical models. Simulation allows experiments for the validation of products, processes or systems design and configuration. Simulation modelling helps in cost reduction, decreases development cycles and increases product quality. To analyse their operations and support decision-making, manufacturers have been using modelling and simulation. Simulation technologies already proved its effectiveness in the approach of several practical real-world problems in manufacturing sector. The domain areas of simulation are shown in Figure 4 with the focus on simulation methods and tools [9].

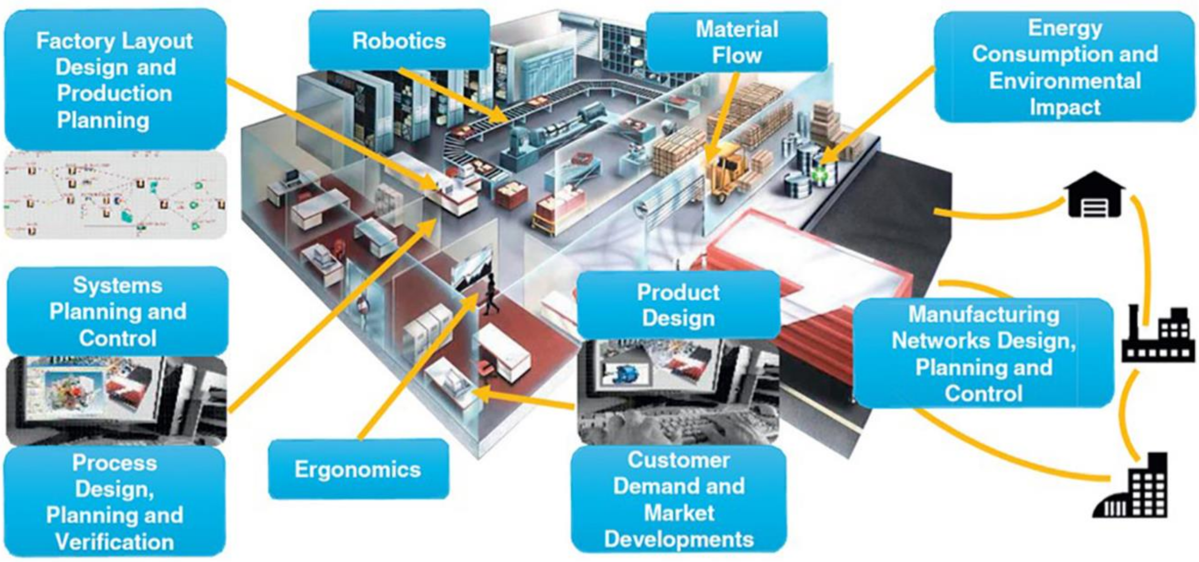

Figure 4: Domains on simulation research of contemporary manufacturing[2]

Figure 5 shows types of simulation models. Choosing and developing the best suitable type of simulation model to represent the real system is a multi-criteria decision-making problem, e.g., static models for modelling a structure without activity and dynamic models for investigating the behaviour of a system evolving through time.

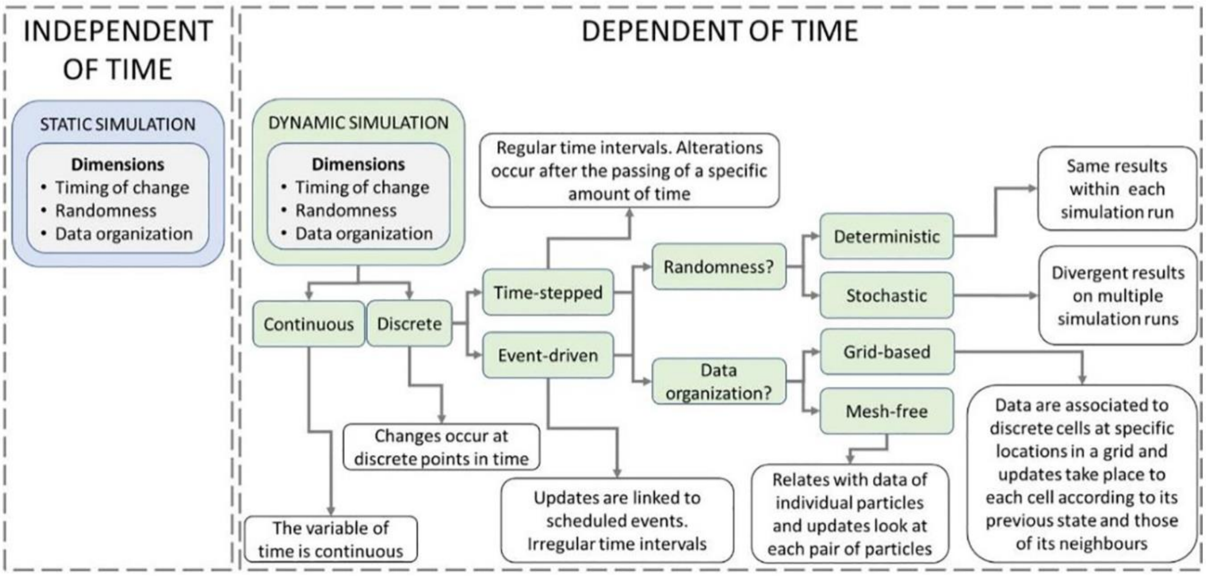

Figure 5: Types of simulation. Based on [9]

3.1.5 Cloud, Fog, Edge Computing

Cloud computing is the on-demand availability of computer system resources, especially data storage (cloud storage) and computing power, without direct active management by the user [5]. The term is generally used to describe data centres available to many users over the Internet. Large clouds, predominant today, often have functions distributed over multiple locations from central servers. If the connection to the user is relatively close, it may be designated an edge server. Clouds may be limited to a single organization (enterprise clouds) or be available to multiple organizations (public cloud). Cloud computing relies on sharing of resources to achieve coherence and economies of scale. Advocates of public and hybrid clouds note that cloud computing allows companies to avoid or minimize up-front IT infrastructure costs. Proponents also claim that cloud computing allows enterprises to get their applications up and running faster, with improved manageability and less maintenance, and that it enables IT teams to more rapidly adjust resources to meet fluctuating and unpredictable demand, providing the burst computing capability: high computing power at certain periods of peak demand. Cloud providers typically use a "pay-as-you-go" model, which can lead to unexpected operating expenses if administrators are not familiarized with cloud-pricing models. The availability of high-capacity networks, low-cost computers, and storage devices as well as the widespread adoption of hardware virtualization, service-oriented architecture and autonomic and utility computing has led to growth in cloud computing. As of 2017, most cloud computers run a Linux-based operating system.

Fog computing, also called Edge Computing, is intended for distributed computing, where numerous "peripheral" devices connect to a cloud. (The word "fog" suggests a cloud's periphery or edge). Many of these devices will generate voluminous raw data (e.g., from sensors), and rather than forward all this data to cloud-based servers to be processed, the idea behind fog computing is to do as much processing as possible using computing units co-located with the data-generating devices, so that processed rather than raw data is forwarded, and bandwidth requirements are reduced. An additional benefit is that the processed data is most likely to be needed by the same devices that generated the data, so that by processing locally rather than remotely, the latency between input and response is minimized. This idea is not entirely new: in non-cloud-computing scenarios, special-purpose hardware (e.g., signal-processing chips performing Fast Fourier Transforms) has long been used to reduce latency and reduce the burden on a CPU. Both cloud computing and fog computing provide storage, applications, and data to end-users. However, fog computing is closer to end-users and has wider geographical distribution.

3.1.6 Artificial Intelligence, Machine Learning and Deep Learning

Machine learning (ML) is the study of computer algorithms that improve automatically through experience and using data. It is seen as a part of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so. Machine learning algorithms are used in a wide variety of applications, such as in medicine, email filtering, speech recognition, and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks. A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning. In its application across business problems, machine learning is also referred to as predictive analytics.

Deep learning (also known as deep structured learning) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised. Deep-learning architectures, such as deep neural networks, deep belief networks, deep reinforcement learning, recurrent neural networks and convolutional neural networks, have been applied to fields including computer vision, speech recognition, natural language processing, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.

Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analogue.

The adjective "deep" in deep learning refers to the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, but that a network with a no polynomial activation function with one hidden layer of unbounded width can. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

3.1.7 Virtual, Augmented, and Extended/Mixed Reality (XR)

The aim of XR is to increase human performances, supplying the needed information to a given specific task. This novel technology provides powerful tools, acting as an interface between human and machines and products. AR technology can be found on a wide range of sectors, e.g., entertainments, marketing, tourism, surgery, logistics, manufacturing, maintenance and quality control. As a growing evolving technology, recently, XR usage is spreading to different manufacturing fields [10]. The use of XR on manufacturing processes regarding to simulation, assistance and guidance has been proven to be an efficient technology helping on problems. XR technology increase reality operator's perception by making use of artificial information about the environment, where the real world is fulfilled by its objects. As long as it interacts with human senses, XR can make use of any kind of hardware. Using XR can help on closing some gaps, e.g., between product development and manufacturing operation, due to the ability to reproduce and reuse digital information and knowledge at the same time that supports assembly operations. Based on [11,12], Figure 7 shows the most relevant tasks related to industrial environments and manufacturing fields where the AR brings value.

Figure 6: XR in non-destructive testing on pipelines: an example [10].

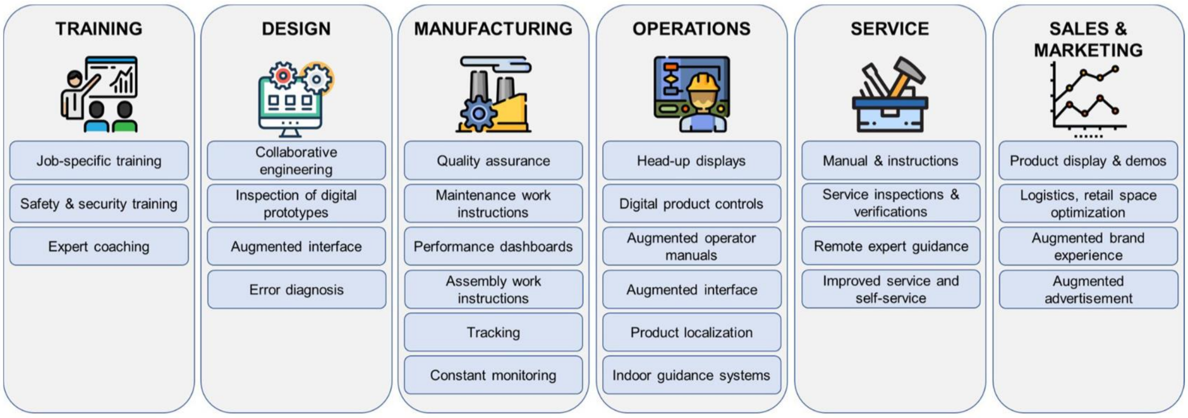

Figure 7: Value of industrial XR across I4.0. Based on [11,12]

3.1.8 Robotics and Cobotics

Robotics is an interdisciplinary field that integrates computer science and engineering. Robotics involves design, construction, operation, and use of robots. The goal of robotics is to design machines that can help and assist humans. Robotics integrates fields of mechanical engineering, electrical engineering, information engineering, mechatronics, electronics, bioengineering, computer engineering, control engineering, software engineering, mathematics, among others. The traditional classification of robots is based on their morphology, which usually allows a visual and functional representation of their use:

- Robotic arm: It is made of a serial kinematic chain.
- Parallel robot: Robot with ending components linked to the base by several independent kinematic chains.
- Cartesian robot: Robot with prismatic articulations in which axes are placed according to Cartesian coordinates.

- Mobile robot: Robot that can move from its original position.
- Exoskeleton: Robot worn by a human to improve its performance or mitigate his handicap.
- Hybrid robot: Combination of the above.

There are other classification methods. One of them is based on the “intelligence” of the robot, as it is proposed by the American Robotic Industries Association and the JIRA (Japan Industrial Robot Association). The basic robot is an open loop command system and the most sophisticated is able to elaborate a complex planning process.

“Cobotics” is a neologism formed by the “collaborative” and “robotics” terms. It has been used for the first time in 1999 by Peshkin and Colgate to conceptualize the direct interaction between a robot and a human on a dedicated workstation [13]. Its meaning evolved towards different definitions according to the context of the application. A cobot is defined as a robot that has been designed and built to collaborate with humans. A workstation including a robot and a human collaborating is called a cobotic system. Cobotics is defined by the science and techniques of designing, building, studying and evaluating cobotic systems. A robot may have all mechanical and hardware characteristics for a possible collaboration with humans but if it used in full autonomy, it is not part of a cobotic system even if it can be called a cobot.

3.1.9 Additive manufacturing (AM)

3D printing, or additive manufacturing, is the construction of a three-dimensional object from a CAD model or a digital 3D model [2]. The term "3D printing" can refer to a variety of processes in which material is deposited, joined or solidified under computer control to create a three-dimensional object, with material being added together (such as plastics, liquids or powder grains being fused together), typically layer by layer.

In the 1980s, 3D printing techniques were considered suitable only for the production of functional or aesthetic prototypes, and a more appropriate term for it at the time was rapid prototyping. As of 2019, the precision, repeatability, and material range of 3D printing have increased to the point that some 3D printing processes are considered viable as an industrial-production technology, whereby the term additive manufacturing can be used synonymously with 3D printing. One of the key advantages of 3D printing is the ability to produce very complex shapes or geometries that would be otherwise impossible to construct by hand, including hollow parts or parts with internal truss structures to reduce weight. Fused deposition modelling (FDM), which uses a continuous filament of a thermoplastic material, is the most common 3D printing process in use as of 2020.

3.1.10 Blockchains and cybersecurity

The world relies on technology more than ever before. As a result, digital data creation has surged. Today, businesses and governments store a great deal of that data on computers and transmit it across networks to other computers. Devices and their underlying systems have vulnerabilities that, when exploited, undermine the health and objectives of an organization.

A data breach can have a range of devastating consequences for any business. It can unravel a company’s reputation through the loss of consumer and partner trust. The loss of critical data, such as source files or intellectual property, can cost a company its competitive advantage. Going further, a data breach can impact corporate revenues due to non-compliance with data protection regulations. It’s estimated that, on average, a data breach costs an affected organization $3.6 million. With high-profile data breaches making media headlines, it’s essential that organizations adopt and implement a strong cybersecurity approach.

A blockchain is a type of database. A database is a collection of information that is stored electronically on a computer system. Information, or data, in databases is typically structured in table format to allow for easier searching and filtering for specific information. One key difference between a typical database and a blockchain is the way the data is structured. A blockchain collects information together in groups, also known as blocks, that hold sets of information. Blocks have certain storage capacities and, when filled, are chained onto the previously filled block, forming a chain of data known as the "blockchain." All new information that follows that freshly added block is compiled into a newly formed block that will then also be added to the chain once filled.

A database structures its data into tables whereas a blockchain, like its name implies, structures its data into chunks (blocks) that are chained together. This makes it so that all blockchains are databases but not all databases are blockchains. This system also inherently makes an irreversible timeline of data when implemented in a decentralized nature. When a block is filled it is set in stone and becomes a part of this timeline. Each block in the chain is given an exact timestamp when it is added to the chain.

3.1.11 System architectures

Several standardization bodies, industrial consortia and research groups actively work in the field of system architectures for I4.0 to provide possible solutions for overcoming the layered structure with the aim of making system interaction more dynamic and flexible [14]. In [15], a state of the art review of I4.0 reference architectures is provided:

- **Industrial Internet Reference Architecture (IIRA)** is a domain-independent, industry-driven architecture that includes manufacturing, healthcare, energy, smart city, and others, and has been developed by the US-led Industrial Internet Consortium (IIC), which has invested in the worldwide adoption of IoT in the industrial context, through what is called Industrial IoT (IIoT).
- **Reference Architectural Model Industrie 4.0 (RAMI 4.0)** is a domain-specific, government-driven architecture and is also the international technical specification IEC PAS 63088:2017. A consortium led by the Association of German Engineers (VDI) and German Electrical and Electronic Manufacturers' Association (ZVEI) has designed RAMI.
- **Industrial Value Chain Reference Architecture (IVRA)** is a conceptual architecture maintained by the Industrial Value Chain Initiative, Japan.
- **Stuttgart IT-Architecture for Manufacturing (SITAM)** is an academic, multi-layered architecture designed within several research projects led by the University of Stuttgart, Germany.
- **LAsim Smart Factory (LASFA)** is a two-dimensional architecture proposed by the University of Ljubljana, Slovenia.
- **IBM Industry 4.0 reference architecture** is a commercially distributed architecture.
- Smart Manufacturing Ecosystem (SME) by NIST
- Intelligent Manufacturing System Architecture (IMSA) by MIIT and SAC
- Framework for Cyber-Physical Systems (F-CPS) by NIST
- Internet of Things Architectural Reference Model (IoT-ARM) by IoT-A project

3.2. Strategic plans and roadmaps

The increasing number and complexity of technologies being developed to cope with the societal challenges of the 21st century calls for structured methodologies for technology management. As information and communication technologies (ICT) facilitate the networked manufacturing systems, implying interoperable systems, information interchange, and decentralized control and decision-making, the need for coordinated efforts among industries and countries is more important than ever. For this purpose, technology roadmaps, whether on an industrial, national and even supra-national levels, have been designated to support the delineation of strategic research agendas [16]. In the following sections, an overview of a number of technology roadmaps and strategic research agendas in ENHANCE partner countries is presented. This is useful to understand the drivers and motivations, to put in perspective and to determine synergies between national and international industry 4.0 initiatives.

3.2.1 European strategic plans and roadmaps

European Member States and regions are committed to adapt their innovation systems to the trends of Industry 4.0. Europe is facing the challenge of finding a balance between promoting research and innovation excellence and putting less advanced regions in the position to benefit from the ongoing industrial revolution [16]. Technology has been underlined by European countries as of fundamental importance for addressing the challenges involved in boosting Europe's economy and to foster job creation.

The European Technology Platforms (ETPs) are forums of industry stakeholders, recognized by the European Commission, and formed to support the development of innovation agendas and technology roadmaps for several sectors, at national and EU levels [17]. Manufuture, the ETP dedicated to improve the competitiveness of European manufacturing, launched the European Factories of the Future Association (EFFRA), a Public-Private Partnership (PPP) of industrial associations, which regularly publishes strategic technology roadmaps that form the basis for research and technology development call topics [16].

Santos et al. (2017) reviewed publications about strategic technology roadmaps issued by the European Commission, related organizations, and Technology Platforms. Roadmaps prior and after the emergence of Industry 4.0 term (in 2011) were considered. The study targeted those technology roadmaps that particularly address the implications to industry and manufacturing. Out of this study, the authors categorized the drivers, design principles and expected achievements of industry 4.0.

- The drivers for the implementation of Industry 4.0 can be categorized in four types: organizational, technological, innovation and operational. The organizational drivers are related to new forms of work and collaboration, while technological drivers result from the convergence of multiple streams. Innovation drivers are forcing the development of new business models and extended innovation networks. Finally, operational drivers derive from the continuous need of organizations to improve their operational performance to remain competitive.
- Six major design principles rule the conceptualization and implementation of Industry 4.0: interoperability, virtuality, real-time capability, decentralization, service orientation and modularity. These design principles can support organizations in the identification of the most appropriate solutions for their businesses.
- Influenced by those drivers and governed by Industry 4.0 design principles, a number of potential realizations can be envisioned. These realizations represent potential materializations and possible scenarios for the implementation of Industry 4.0 pilots in companies. Overall, they point to an increasing relevance of collaborative networks, synchronicity between supply and demand, personalization in product and service development, decentralization, and extensive data use in driving operational performance.

In order to contribute to the economic literature on the fourth industrial revolution, Ciffolilli & Muscio (2018) provided a classification of Industry 4.0 enabling technologies. Then, based on original data on EU financed research and technology development projects from European regions' participation in collaborative research projects promoted by the 7th Framework Programme for research and innovation, they shed light on how the capacities to develop such enabling technologies are distributed in Europe and where the advantages in terms of knowledge creation lie. The authors particularly establish that much of Europe's capabilities are based on the industrial strength of a small group of nations, while there are many regions and Member States in which such capacities are absent. However, the authors highlighted that this is not an unusual situation with respect to other European industries, but it indicates that the diversity of Europe's industrial systems is a key aspect to consider in designing suitable policy actions in support of Industry 4.0, and it is crucial that regional differences are not overlooked.

3.2.2 Tunisian strategic plan and roadmap

As reported by the Tunisian Institute for Competitiveness and Quantitative Studies (ITCEQ) since 2015, Tunisian Manufacturing Industries are one of the key sectors of the Tunisian economy, contributing up to 17% of GDP and employing nearly 1/3 of the working population. They play an important role in creating added value and jobs [19]. Considering the role that digitization can play in accelerating administrative procedures and improving the competitiveness of companies, the ITCEQ has reserved a specific module for it in its 2019 business climate and business competitiveness survey. The study targeted a sample of 1,200 private structured companies operating in industry and services, spread across Tunisia. 1,077 companies responded to the survey, for a response rate of 90%. The results of this survey are available on the ITCEQ website [20]. To determine the status of Tunisian companies in terms of digitization and digital transition, ITCEQ included questions relating to two indicators on the effective digitalization of companies: their use of online administrative services and their efforts to develop a digital transition strategy (online sales, the use of artificial intelligence, big data, etc.).

Regarding the first indicator, the results show that companies increasingly adhere to e-government services. As for the second indicator relating to the development of a digital transition strategy, the results show that nearly half of companies have not adopted one. These companies that have not pursued such a strategy are more prominent at the industry level (54%) and at the SME level (49%). When asked about the main obstacles to the digital transition, 43% of the companies concerned mentioned the complexity of digital transition projects and 21% cited the lack of financial resources as well as the lack of skills [20].

Consequently, Tunisia elaborated a development strategy for its economic competitiveness, considering the post-revolution and post-Covid19 situation. The success of the strategy depends mainly on [21]:

- The development of new technologies
- The improvement of post-industrialization processes and increase in added value
- The transition to a new logistics management
- Dealing with ecological issues and climate change
- The improvement of well-being and socio-economic stability

The first three challenges are among the missions of the Tunisian Agency for the Promotion of Industry and Innovation (APII) and the Tunisian Ministry of Energy and Mines. They constitute the objectives of the implementation of the Industrial and Innovation Strategy 2035 through the following mechanisms [21]:

- The development of the fields of digital technology, artificial intelligence and industry 4.0
- Innovation and the development of new products with high added value through the promotion of R&D.
- The improvement of lead times, mainly for export, via the development of the logistics chain
- The development of industry-oriented research and development funding mechanisms and innovative project ideas (crowdfunding is an example)
- The development of value chains for a move upmarket in industrial output

To deploy the strategy, Tunisia is particularly making efforts to:

- Change its business model and move towards a new Business to Consumer (B2C) model

- Define a new industrial strategy capable of responding to the requirements of the new industrial era but also to the wishes and expectations of companies.
- Promote the transition to "all digital"

Therefore, Tunisia revised its public policies in place and established new development plans, like the quinquennial Economic and Social Development Plan, the new investment law, the “Digital Tunisia 2025” strategy, the strategy for setting up the Electricity-Gas Smart Network or "Smart Grid". New legislative texts affecting private investment and/or priority sectors have also been decreed, such as the law on Public Private Partnerships PPP (2015-49), the banking law (2016-35), the law on competition (2015- 36), the Law on Renewable Energies (2015-12), etc.

3.2.3 Moroccan strategic plan and roadmap

Since 2000, Morocco has launched important institutional and economic reforms based on strategies to address market failures in important sectors of the economy. These reforms have included financial incentives (such as tax exemptions), simplifying administrative procedures (for example to facilitate access to land), and launching major public infrastructure projects. Morocco has also strengthened its sectoral policies through sector development plans aimed at enhancing the potential for economic growth and job creation, including in high value-added manufacturing sectors, such as automotive, aeronautics, and pharmaceuticals [22].

The combined effect of these reforms enabled the emergence of a new investment dynamic in strategic sectors, such as agriculture, industry, and energy. In the industrial sector, the Emergence Plan for industry was followed by the National Pact for Industrial Emergence during the years 2009 to 2015, then by the Industrial Acceleration Plan during the period 2014 – 2020. For example, to support the Industrial Acceleration Plan, the government has provided a financial support of about 2% of GDP over 6 years. The government has also offered ad hoc support to attract foreign investors in large private projects likely to generate significant positive externalities. One example is the project to set up a Renault Company plant in Tangiers, which aims to produce and export 400,000 cars per year [22].

In 2019, Moroccan authorities created a special sub commission to elaborate a new development model for the country and to define the contours of this new model based on a participatory and inclusive approach [23]. To ensure diversification, this structural transformation is expected to affect strategic sectors, such as agriculture, industry and services. The modernization of these sectors will have to accelerate, starting with its digitization and strongly developing the value of its products through a competitive and integrated industrial fabric covering all territories. This will only be possible if there is massive access for stakeholders and industrial players to training and access to new production techniques [22].

3.3. Skill requirements elicitation process

In order to determine the requirements elicitation in partner countries, there is a need to requirements elicitation techniques to obtain information from stakeholders. The main techniques which may be used are listed below. These techniques will ensure the clarity of requirements elicitation in order to deliver solutions that end-users find useful and satisfying.

- Literature review (M, P, Q)
- Questionnaire
- Synthesis of skills

4. Maintenance, Production and Quality Engineering in the Era of Industry 4.0

4.1. Maintenance Engineering

In general, maintenance is the activity of maintaining something. Industrial maintenance involves functional checks, servicing, repairing, or replacing of necessary devices, equipment, machinery, building infrastructure, and supporting utilities in industrial, business, and residential installations. IEC 60050-192:2015 defines maintenance as combination of all technical and management actions intended to retain an item in, or restore it to, a state in which it can perform as required.

4.1.1 Evolution of maintenance strategies and management models

To reduce the risk and minimize the consequences of unexpected stops and disruptions in digitalized manufacturing, maintenance must take a key role. Over time, maintenance has evolved from reactive (Maintenance 1.0) to preventive (Maintenance 2.0) and then to condition-based (Maintenance 3.0), to current predictive and prescriptive approach, which is usually denoted as Maintenance 4.0.

Reactive/Corrective Maintenance is the process of restoring assets after unplanned downtime. It includes troubleshooting, disassembling, readjusting, repairing, replacing, and realigning equipment. The purpose of corrective maintenance is to restore systems that have broken down. Corrective maintenance can be synonymous with breakdown or reactive maintenance.

Preventive Maintenance is planned maintenance that prolongs the lifespan of assets, equipment, and infrastructure. Also known as preventative maintenance, it includes adjustments, cleaning, lubrication, repairs, and replacements.

Condition-Cased Maintenance (CBM) involves monitoring equipment performance with visual inspections, scheduled tests, and sensor devices to determine the most cost-efficient time to perform maintenance. Using machine learning, artificial intelligence, and ICT to anticipate asset maintenance requirements, predictive maintenance can help avoid impromptu corrective maintenance by allowing for plant maintenance to be effectively scheduled prior to equipment failure. Both strategies encompass the same maintenance best practices: rely upon data to determine whether upkeep is necessary and prevent unplanned downtime with proactive maintenance.

Predictive and Prescriptive Maintenance not only looks for failure signatures (predictive and condition monitoring for recommendations), but also provides information about how to delay or eliminate equipment failure. Prescriptive maintenance algorithms can comb historical data of a wide variety of operating conditions, and extract patterns and extrapolate data to provide hypothetical operating environments.

Reliability-centred maintenance (RCM) and eventually Total Productive Maintenance (TPM) are example of approaches that make use of the previous methods.

4.1.2 Organization and management of maintenance operations

Maintenance operations are organized and managed through several processes, which will be introduced and explained in the following subsections.

4.1.2.1 Equipment inspection, functional diagnosis, and data acquisition

Equipment and devices can only function properly for a certain period. Therefore, it is extremely important to plan to ensure safe and reliable operation by properly inspecting and diagnosing the equipment [24]. Inspections aim to identify whether an equipment can be operated, adjusted and maintained safely [25]. They help prevent major repairs and equipment failure [26]. The diagnosis involves identifying and quantifying the damage that has occurred on an equipment [27]. Diagnosis is required to evaluate degradation precisely [28]. Existing work on Inspection has concentrated on optimizing inspection intervals, with a specific application to mining equipment [29]. Many fault diagnosis methods have been developed and all fall under two categories: model-based and data-driven approaches [30]. Other relevant concepts around maintenance and faults are fault detection, fault localization, and fault correction. For the latter, suitable data acquisition methodology is vital to specify accuracy of such an approach [31]. However, existing diagnostic methods are mainly applied to rotating machinery and turbines [32–35].

4.1.2.2 *Assessment of equipment lifetime and health*

Lifetime Assessment (LTA) of an equipment examines critical data on its current operation state and provides valuable information on its health. Condition monitoring and Health management of machines represent important development areas for the last several decades [36,37]. Health status of a machine can be well evaluated and characterized by the conventional machine diagnostics and prognostics approaches [38]. In a smart factory, the data captured is transmitted to the factory level database towards the control centre. In the control centre, the data by different sensors is processed and extracted to represent the health status of components and machines, that is health or lifetime assessment [39]. All health monitoring techniques have been applied to manufacturing machines and turbines, mainly wind and gas turbines [40–42].

4.1.2.3 *Ageing models and Remaining Useful Life estimation*

Health prognostics is one of the major tasks in CBM, which aims to predict the Remaining Useful Life (RUL) of machinery based on the historical and on-going degradation trends observed from condition monitoring information [43,44]. The RUL prediction should be triggered from the start time of the unhealthy stage, which is defined as the first predicting time (FPT), [45]. The RUL of machinery is defined as “the length from the current time to the end of the useful life” [46]. Most publications also define the RUL as the time left before the health states of machinery cross a failure threshold (FT), [47,48]. Existing common RUL prediction approaches are organized into four categories according to their basic techniques and prediction algorithms [27,36,38,49–51]: physics model-based approaches, statistical model-based approaches (autoregressive (AR) filtering, Random coefficient models, Wiener process models, Gamma process models, Inverse Gaussian (IG) process models, Hidden Markov models (HMMs), Proportional hazards (PH) models), AI approaches (Artificial Neural Networks (ANNs), Neural Fuzzy (NF) systems, Support Vector Machine (SVM), Relevance Vector Machine (RVM), K-Nearest Neighbor (KNN), Gaussian Process Regression (GPR), etc.) and hybrid approaches (NF systems with HMMs, ANNs with AR, etc.)

4.1.2.4 *Equipment lifetime extension strategies and practice:*

The fundamental methodology for LifeTime Extension (LTE) of large industrial equipment remains a challenge. For one thing, previously installed units have not systematically considered the requirements and procedures of lifetime extension at the first place. For another, the non-destructive flaw quantification and accompanied life assessment methods at the time of manufacturing and commissioning of the equipment components may need serious review according to the standard nowadays [52,53]. There has been a moderate amount of work that has developed equipment LTE. The existing work proposes a lifetime extension methodology for critical components of the considered equipment [54,55], mainly rotating components for turbines [56]. In particular, Siemens developed a lifetime extension methodology for its gas turbines [57]. Within its program, recommendations for lifetime extension are made to the gas turbine operator. The methodology in general consists of identifying critical components, then estimating their RUL and incorporate various uncertainties for risk mitigation [58].

4.1.2.5 *Equipment remanufacturing, repair, and re-use*

Each equipment has its own set of critical components and are generally described as components, subsystems or systems that are vital to the operation of the equipment and the failure of which leads to the failure of the whole equipment or a significant part of it. Therefore, special attention is given to prevent the failure of such components. Remanufacturing is defined as “returning a used product, via a manufacturing-type process, to at least its original performance with a warranty that is equivalent or better than that of the newly manufactured product” [59,60]. The application of remanufacturing can be already seen in some aerospace and automotive industries [61–64]. Though remanufacturing is already an established process in some industries for some types of equipment, there is still a need to further extend the technical options for and show the business case of remanufacturing and re-use in large industrial equipment. The first paper on recycling electrical machines is [65] where early ideas on the topic are presented. The Directive of the European Parliament on waste electrical and electronic equipment (WEEE) introduced new regulations to contribute to sustainable production and consumption of electrical and electronic equipment. European legislative efforts have begun to mandate recycling remanufacturing and re-use of such equipment [66].

4.1.2.6 Equipment refurbishment and upgrading

Asset users, and especially large industrial equipment users, are increasingly being required to proactively manage their equipment in order to extend their life cycle and avoid early replacements [67]. To this respect, equipment's refurbishment and upgrading, understood as the modifications that involve respectively restoring or increasing the functionality of the products [68], appear as an opportunity for asset users to extend equipment life cycle, therefore becoming both more competitive and environmentally sustainable [69]. According to [70], four main properties of the product are suitable to be upgraded: ease of access, ease of identification, ease of handling and wear resistance. In fact, it is central to consider these factors from the design phase [71]. Some specific challenges related to the equipment upgradability, not only at design stages, but also for equipment that have been long operating, can be related either to technical or management aspects. On the one hand, technical aspects regard to modular structures development, reusable components manufacturing or tools for facilitating the upgrade itself [72,73]. On the other hand, management issues regard to decision support systems, such as simulation and optimisation, uncertainty assessment or optimal upgrade levels identification [72,74]. It should also be noted that large industrial equipment refurbishment and upgrading present a business challenge as well, since the longer the assets life cycle, the less equipment manufacturers will sell. This requires manufacturers to change their business if they are to remain competitive, having to focus on service-oriented business models rather than on product-oriented business models.

4.1.2.7 Decision support systems for equipment LTA/LTE

A very few works about software developments to support decision-making for equipment LTA/LTE exists in the industrial and academics literature [75]. A MATLAB Simulink application to simulate the tool life based on the flank wear rate is developed in [76]. Siemens has developed their own off-line monitoring system which can provide measuring data from their feet of machines (turbines specifically) across the world [41,77]. This monitoring system has been used in conjunction with a developed transient computer model for turbines LTA and LTE purposes. Three soft computing methods for the assessment of remaining useful life (RUL) of cutting tools are developed [78].

4.1.3 Application of Industry 4.0 technologies: examples

The literature provides several contributions of industry 4.0 technologies supporting maintenance management. CPS enables real-time monitoring of production assets to connect the physical world with virtual space [79]. These data are transmitted through IoT to develop smart solutions for condition-based maintenance [80,81]. With IoT, the monitoring of operating conditions is more efficient and sustainable, as it avoids the engagement of excessive resources [82]. To demonstrate this, [12] focus on shop-floor scheduling and condition-based monitoring based on data collected from machines and stored on a Cloud platform, where machine tools and human resources are connected through the IoT. In addition, [83] propose a framework for fault diagnosis and prognosis in machine centres, which is composed of a data acquisition module enabled by the IoT and a data pre-processing module operated by a big data warehouse. The IoT guarantees the collection of big data from the operation of the various machines and Cloud technology provides the storage capacity and computation power to process them [84,85].

An additional technology supporting the maintenance process is big data analysis, which provides tools and models to highlight trends and patterns in order to develop an effective maintenance plan. Therefore, the combined use of the IoT and big data analysis can facilitate real-time monitoring of machinery for the early detection of anomalies and predictive maintenance [86–88]. Indeed, big data analysis has been effectively applied to predicting the lifecycle of equipment, tools and robots [89–92]. This application is also confirmed by [93] who introduce the IoT, big data and automated simulation for machinery health monitoring in ship manufacturing. CPS is also the foundation for further virtual representation of digital twin and simulation tools to monitor effectively the health of the machinery workshop, using the data collected from the IoT gateway stored in Cloud [94–96]. In this regard, it is possible to combine digital twin and big data analysis for smart maintenance, repair and overhaul so that the location and diagnosis can be displayed to users and technicians [97].

The use of artificial intelligence techniques can also facilitate fault diagnosis and predictive maintenance [98,99]. [100] propose a combined off and online model for identifying the condition of machinery and forecast deviations by examining different ML algorithms. [79] propose a prescriptive maintenance model (PriMaf) for adapting maintenance activities within the context of CPPS, where deep learning is used to support decision making and learning from multi-dimensional data sources.

Regarding Visualization technology, [101] and [102] highlight the potential of using augmented reality to support maintenance training tasks, while [103] evaluate the implementation of Industrial Augmented Reality (IAR) in effectively detecting anomalies and identifying problems. [104] also discuss the benefit of the ultra-low latency and high reliability offered by 5G for field personnel using augmented reality devices for conducting maintenance and repair tasks.

Several German and H2020 research projects are addressing the benefits of AI for maintenance processes in industrial environments:

AssetUp4.0 - Edge intelligence for condition monitoring and status visibility of assets in harsh industrial environments (EU-EIT Manufacturing, https://www.assetup40.eu/) is a project aiming to bring a new software solution for condition monitoring and predictive analytics to the market. The focus relies on a systematic approach, combining the relevant AI algorithms, concepts, and specific solution into an industrial ecosystem. This project will deliver a novel distributed and resilient platform for production and process data ingestion and intelligence (with a focus on predictive maintenance and augmented reality for maintenance), based on micro services and federated machine learning. Additionally, containerisation technologies will provide an abstraction layer enabling scalability, resilience and flexibility.

AutoCBM - Automated Adaption of Condition-Based Maintenance methods for Manufacturing Systems (German funded research project, https://www.assetup40.eu/)). The aim of the project is a partial automation of the specific development process so that analysis methods for condition-based maintenance can be transferred to other machines and plants with less effort. AI-based Methods and conventional stochastic time series analysis are to be combined to form adaptive algorithms that enable the automated detection of anomalies in the operating behaviour of manufacturing machines. User-friendly software will be developed to select suitable diagnostic models and relevant data characteristics on the basis of a meta learning procedure, monitors machine data and presents relevant information to the user.

MetaMaintain - A meta-learning approach to select appropriate prognostic methods for the predictive maintenance of digital manufacturing systems (German funded research project). The objective of the project is to develop a meta-learning system that allows an automated selection of the best suitable forecasting method. The results of the forecasts will eventually be used for an integrated production and maintenance planning. In addition, a monitoring and adaptation procedure is to be implemented to trigger a dynamic adaptation of the system to new system states. In this way, forecasting methods can be selected dynamically and optimal maintenance decisions can be derived based on the current state of a production system.

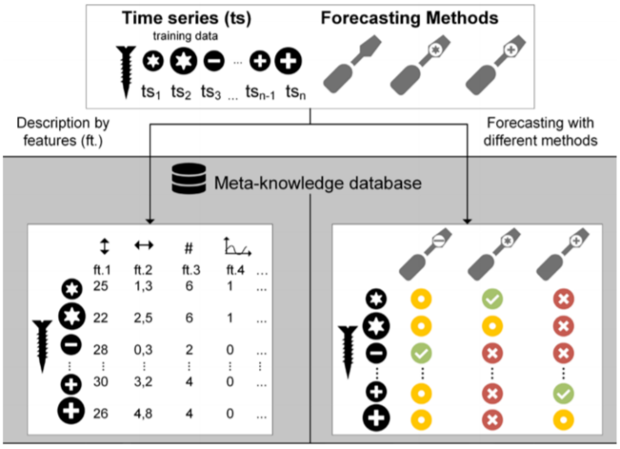

Figure 8: MetaMaintain concept. Source: BIBA project description

compARe - Optimization of the maintenance of wind turbines by using image processing methods on mobile augmented reality devices (German funded research project). Maintenance ensures the safe and reliable operation of wind turbines generators (WTG). A high level of technical availability ensures the economic operation of WTGs and the secure supply of electricity from renewable energies. The condition of individual components is assessed and documented by the service technicians using visual inspection. Condition monitoring plays a decisive role in critical components. Their failure can lead to the shutdown of a wind turbine or even entire wind farms. However, defects to the components often progress very slowly and are therefore difficult to detect. Examples of such applications are the monitoring of cast components for crack formation, the inspection of critical cable connection points, or the temperature control of bearings, converters, and cable systems. Objective In the funded project compARe, an ARbased technical assistance system is developed that uses image processing methods to support service technicians in the maintenance of wind turbines. The project will focus on tasks that only allow defect detection by comparing the current status with a previously documented status or a target status. Thus, the system can help avoid damage to the WTG and increase maintenance measure's efficiency. Approach Employing AI-based image processing methods, such as Convolutional Neural Networks (CNN), defects in components can be detected, classified, and evaluated. Furthermore, the comparison of component states based on historical data is possible. Mobile assistance systems have proven to be very promising for the support of service technicians in wind energy. The use of these computing-intensive image processing methods on mobile devices is a challenge. However, it offers great potential in combination with mobile Augmented Reality (AR) technology. In this way, virtual information on the change of component conditions can be provided directly about the components concerned in the field of vision of the service technicians.

ReaLCoE - Next Generation 12+MW Rated, Robust, Reliable and Large Offshore Wind Energy Converters for Clean, Low Cost and Competitive Electricity (H2020 funded research project). The aim of this project is to install, demonstrate and operate a technology platform and prototype of an innovative and digitised 12+MW WEC with significantly reduced LCoE. Optimised logistic and installation processes as well as an overall interoperable Industry 4.0 and IoT system will substantially contribute to this objective. Besides a digital twin of each individual WEC this contains also a holistic condition-based monitoring system and predictive maintenance tools for more efficient maintenance processes. As a key element of ReaLCoE, BIBA focusses on the digitisation of future offshore WECs and their connection with the adhered value chain. Besides the integration of sensors and the creation of information feedback loops between the turbines and the IT systems, the digital representation of the WECs through a digital twin takes a major part in BIBAs contribution to ReaLCoE. In combination with technologies for predictive and condition based maintenance, these measures lead to significant improvements in terms of increased component reliability and reduced maintenance costs. Furthermore, BIBA will develop new installation concepts and conducts various performance simulations.

The literature analysis shows, and experienced researchers confirm that deploying presented data-driven maintenance strategies and concepts creates many new opportunities for improving maintenance processes and therefore satisfying SME needs in the era of industry 4.0. The improvements concern all dimension of sustainability are presented in Table 2. Sustainable development (SD) is defined as development that meets the needs of the present without compromising the ability of the future generation to meet their own needs [105].

Table 2: Benefits in Maintenance 4.0 confronted with SD dimensions[105]

	Potential benefits	Description
Economic dimension	Improves economic efficiency	Novel maintenance strategies can reduce machine downtime and the cost of unplanned downtime. Regular maintenance of machines and systems can increase their service life
	Reduces maintenance time	Continuously evaluation of the captured data makes it possible to determine the best time for an upcoming maintenance. Automatic reports for maintenance scheduling and proactive repairs reduce maintenance time and de-creases overall maintenance costs
	Improves machine performance	The permanent analysis of the collected data makes it possible to improve the performance of the machine and achieve higher productivity in the long run
	Decreases spare parts inventories	3D printing can provide benefits in spare parts creating, particularly it is good solution when parts that are discontinued are needed.
Environmental dimension	Decreases spare parts and lubricant utilization	With condition-based, predictive and mainly prescriptive maintenance worn equipment parts are replaced only when necessary, lubricants are changed only as needed, rather than on a fixed schedule for planned or preventive maintenance
	Improves environmental safety	Breakdowns of machinery can lead to catastrophic events. By predicting issues before they escalate, it will be able to reduce environmental impact
	Minimizes end of life waste	Predictive and prescriptive maintenance promoted by big data analytics extends the lifespan of machinery.
	Optimizes energy consumption	Enhancing ecological footprint by better gauging and controlling energy consumption and environmental conditions for energy conservation.
Social dimension	Implements new educational model	Through virtual reality, it is possible to educate operators, by teaching the right operations to do for maintenance or machine setup. The augmented reality system aims to replace old paper manuals that are difficult to under-stand
	Improves worker safety	Breakdowns of machinery can lead to catastrophic events and harm workers. By predicting issues before they escalate, it will be able to reduce accidents and boost team morale
	Improves working condition	Through the application of VR/AR it is possible to obtain additional information and to proactively assess different variants of maintenance processes realization to optimize the key factors of the given operation of manual work, visibility, accessibility, usability of equipment, comfort and risk factors
	Improves workers satisfaction	Work performed in safe and healthy conditions improves the efficiency of the maintenance staff and increases their motivation and efficiency

4.1.4 Required capabilities

Table 3: Concepts and corresponding requirements and needs for Maintenance 4.0

Maintenance Concepts	Maintenance Concept's Requirements	Expected Capabilities
Adoption of adequate/novel maintenance strategies	Understand the evolution of strategies, use of enabling technologies such as AI, CPS and novel interaction technics	• Understanding and Deployment of novel Inspection Techniques • Requirement Engineering • Product Lifecycle Management • Product design/ Computer Aided Design for X • Modelling • Big data-driven Optimisation and Simulation • Standards/regulations • Planning and Control • Scheduling • Project management • Information and Communication Technologies • Near real-time/ real-time Computing • Decision-making Systems • Predictive Analytics • Forecasting • Prognosis • Business Intelligence • Data/information/knowledge Acquisition/Interpretation/Handling • System Integration • Interoperability • Visibility and Traceability • Safety and Security • Collaboration and Communication
Equipment inspection, functional diagnosis, and data acquisition	Understand engineering of equipment, sensors, data manipulation, statistics	
Assessment of equipment lifetime and health	Understand component degradation and failure modes, data analysis, knowledge of condition assessment methods, risk-based asset management, develop life estimation algorithms, planning and operations scheduling	
Ageing models and Remaining Useful Life estimation		
Equipment lifetime extension strategies and practice		
Equipment remanufacturing, repair, and re-use	Understand engineering and design of equipment, production planning, quality assessment, operations sequencing and optimization	
Equipment refurbishment and upgrading		
Decision support systems for equipment LTA/LTE	Understand MC0/MC1/MC2/MC3 + practice organizations information systems, understand and practice decision-making aid	

Table 4: Contribution of main I4.0 technologies to selected maintenance concepts

Technologies / Maintenance Concepts	IIoT, CPS	BDA	Simulation/ Emulation	Cloud/Edge/ Fog Computing	AI/ML/DL	AR/VR/XR	Robots/Cobots	Additive Manufacturing	Cyber Security	Technologies / Maintenance Concepts related requirements
Adoption of adequate/novel maintenance strategies	***	***	**	**	***				*	Understand the evolution of strategies, use of enabling technologies such as AI, CPS, and novel interaction technics
Equipment inspection, functional diagnosis, and data acquisition	***	***	***	**	***	**	*		*	Understand engineering of equipment, sensors, data manipulation, statistics
Assessment of equipment lifetime and health	***	***	***	**	***	**			*	Understand component degradation and failure modes, data analysis, knowledge of condition assessment methods, risk-based asset management, develop life estimation algorithms, planning and operations scheduling
Ageing models and Remaining Useful Life estimation	***	***	**	***	***	**				
Equipment lifetime extension strategies and practice	***	***	***	***	***	**			*	
Equipment remanufacturing, repair, and re-use	***	**	**			**	*	***		Understand engineering and design of equipment, production planning, quality assessment, operations sequencing and optimization
Equipment refurbishment and upgrading	***	**	**			**	*	***		
Decision support systems for equipment LTA/LTE	***	***		***	***	**			*	All mentioned skills + practice organizations information systems, understand and practice decision-making aid

Legend: * (low), ** (intermediate/mitigate),*** (high)

4.2. Production Engineering

4.2.1 Concepts, models and practices

4.2.1.1 Digital Twin: A central technological element for digitalisation

Several works in the manufacturing field exploit the DT to optimize all aspects of the product manufacturing process and process lifecycle, focusing on the areas of design, production planning and control, prognostics, and life-cycle management, etc. where DTs demonstrate superiority over the traditional solutions. DTs are useful for the digitalization of production facilities and paradigm shift. The DT approach has attracted strong interests from research and industry practitioners. The PREDIX platform, developed by GE, that can better understand and predict asset performance [106]. SIEMENS's focus covers smart operations during the complete process of product design, production and operation [107]. ABB emphasizes on enabling data-driven decision makings [108]. Microsoft also geared up its Digital Twin product portfolio, providing a ubiquitous IoT platform for modelling and analysing the interactions between people, spaces, and devices [109]. Initiatives from these technology leaders have significantly pushed the boundary of Digital Twin for engineering applications.

4.2.1.1.1 Digital Twin for Machine Life-Cycle Improvement

The most applications adopting the DT approach are related to the management of machine lifecycle. The prediction of the structural life of the aircraft through multi-physics modelling, multiscale damage modelling, integration of the structural finite-element model (FEM) and damage models, uncertainty quantification, and high-resolution structural analysis has been addressed. Within their DT approach, Tuegel et al. proposed a new concept, the Airframe Digital Twin (ADT), to maintain airframe, reduce uncertainty, and improve robustness [110,111]. A DT model based on the dynamic Bayesian network to more accurate diagnosis and prognosis of the operational state of aircraft wings has been built by Li et al. [112]. Zakrajsek and Mall built a DT model to predict the tire touchdown wear and the probability of failure. The DT model demonstrated many advantages over the traditional model in predicting the probability of failure for the varying sink rate, yaw angle, and speed [113]. Glaessgen and Stargel called for new DTs that could integrate historical data, fleet data, and sensor data. DTs attributes such as the ultrahigh-fidelity model, the high computational and data processing ability, and vehicle health management system have been considered as well as the benefits for the prognosis and health management (e.g., increase of reliability, and timely assessment of mission parameters) [114]. Gabor et al. developed a simulation-based DT model to predict the behaviours of a cyber–physical system [115].

Knapp et al. applied the DT in an additive manufacturing process to predict the cooling rate, temperature gradient, micro hardness, velocity distribution, and solidification parameters. As a result, it led to more accurate predictions of the cooling rate and melting rate than the level set method and heat conduction models [116]. Reifsnider and Majumdar built a high-fidelity DT model, based on the multi-physics simulation, to perform fault diagnosis without damage initiation. demonstrated high sensitivity to fracture development, and was therefore, useful for the health monitoring [117].

Cerrone et al. presented the as-manufactured geometry to predict crack paths. A specimen DT model was created to deal with the ambiguity of crack paths under the shear loading, which led to more accurate predictions [118]. Gockel et al. built the DT of an aircraft structure by using the models of FEM and computational fluid dynamics (CFD). They suggested that the DT could reduce cost and improve reliability [119]. Bielefeldt et al. combined the techniques of shape memory alloy, sensory particles, and finite-element analysis to detect, monitor, and analyse the structural damage of commercial aircraft wings [120].

4.2.1.1.2 Digital Twin for Cyber Physical Production System design

An overview of technologies that create DT in CPPS is shown in Figure 9. CPPS is a combination of both logical and physical components that can be characterised by continuous and discrete dynamics. In addition, modelling and implementing a digital twin may require skills from multiple disciplines, such as electromagnetism, fluid dynamics, and kinematics etc., to capture physical properties of the manufacturing process. Therefore, a modelling technique with varying levels of abstraction would be needed for both flexibility and expressiveness.

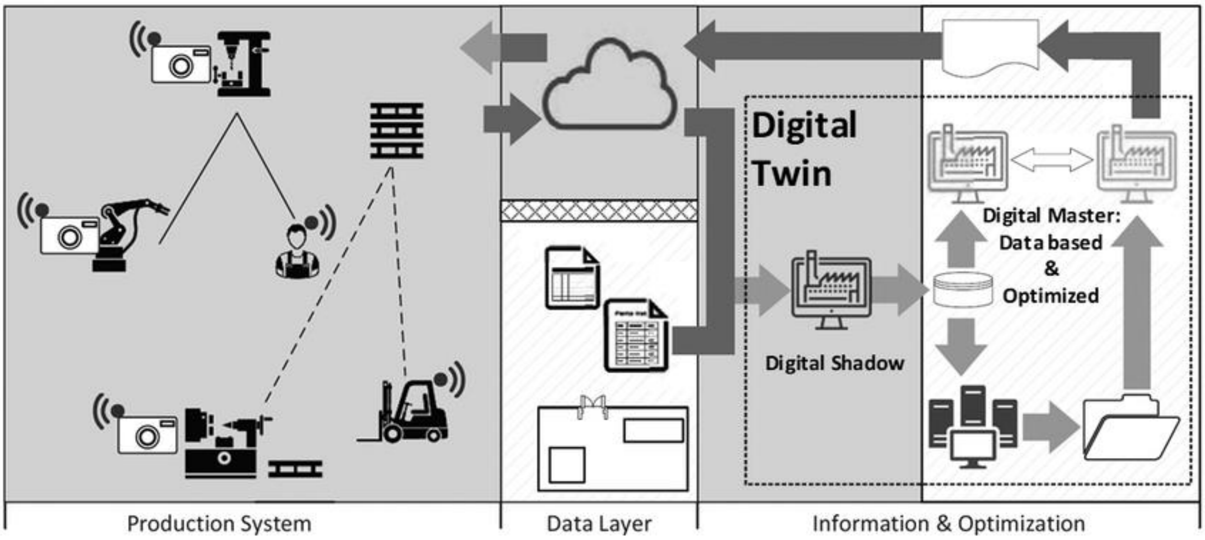

Figure 9: Concept of the CPPS through the Digital Twin in SMEs-adapted [121]

DTs can be used to design new products in a more responsive, efficient, and informed manner. Zhuang et al. explored the application of DTs in product design and suggested some relevant theories and tools to implement the design-oriented DT [122]. Canedo[123] considered DTs as a new way of managing the Industrial IoT. They argued that the product design could be notably improved by adding the data feedback from DTs. Design and production can be synchronized through DTs. Yu et al. proposed a new DT model to manage the 3-D product configuration. The application of DTs in design could reinforce the collaboration between design and manufacturing [124]. Tao et al. proposed a DT-driven design framework because most of the design decisions were made without adequate interactions among the expected, interpreted, and external spaces. They envisioned some potential DT applications in different design phases such as product planning, conceptual design, and detailed design. A case study on bicycle design was conducted to instantiate the framework [125]. Schleich et al. put forward a new DT model to manage geometrical variations and support designers to evaluate the quality of a product even at the early stage [126]. Zhang et al. proposed a DT-based approach to design the production lines. A case study on the glass production line was used to validate the effectiveness of the approach [127]. DTs can make a production process more reliable, flexible, and predictable. DTs can visualize and update the real-time status, which is useful for monitoring a production process. DTs play a critical role in developing advanced cyber-physical production systems. Since DTs can synchronize the physical and virtual spaces, human operators can depend on DTs to monitor a complex production process, make timely adjustments, and optimize the process. Tao and Zhang developed the DT of a shop floor, which included the physical shop floor, virtual shop floor, shop floor service system, and production data. Besides, they envisioned how DTs could serve intelligent manufacturing [125].

Ameri and Sabbagh described how a "digital factory", the DT of a physical factory, was developed in terms of capability extraction, supply chain, and digitalization process [128]. Soderberg et al. discussed the DT application in real-time geometry assurance during the preproduction and production phases, based on a case study of the sheet metal assembly station [129]. Konstantinov et al. discussed how to adapt existing tools to enable DTs and applied a set of virtual engineering tools (e.g. vueOne) to optimize a magnet insertion process [130]. Vachalek et al. focused on the DT-driven optimization of production lines of pneumatic cylinders [131]. Uhlemann et al. presented a data acquisition approach to implement DTs in production systems. In this way, it realized the effective production control in real time [132].

Table 5: Digital Twin Use-Case Scenarios

Features	**Examples and References**

Health monitoring and forecasting	- Life prediction of aircraft structure, detection and prediction of cracks in a non-standard material test specimen[110] [111] - Accurate diagnosis and prognosis for operational state of aircraft wings [112] - Vehicle health management system [114]. - High sensitivity to fracture monitoring [117]. - Cost saving and reliability improvement of aircraft structures by using finite-element model (FEM) and computational fluid dynamics (CFD) [119] - Detecting, monitoring, and analysis of the structural damage of commercial aircraft wings [120].
Root-cause failure analysis and prediction	- Detection of a faulty valve [133] - Data-oriented analysis and prediction for wind turbines - Impact of state changes on upstream and downstream processes of a production system, Identification and evaluation of anticipatory maintenance measures, Evaluation of machine conditions based on descriptive methods and machine learning algorithms, better transparency of a machine's health condition [134] - Predict tire touchdown wear and probability of failure for the varying sink rate, yaw angle, and speed [113] - Crack paths prediction [118]
Product design / Layout planning	- DT-based bicycle design [135]. - 3D product configuration - Data feedback from DTs for product design improvement [123] - Geometrical product variations management: quality engineering [126] - Continuous production system evaluation and planning [121]
Production planning, control and optimisation	- Glass production line design [127] - Orders planning based on statistical assumptions - Improved decision support by means of detailed diagnosis - Automatic planning and execution from orders by the production units [136] - DTs serving intelligent manufacturing [125] - real-time geometry assurance during the preproduction and production: Sheet metal assembly station [129] - Magnet insertion process optimisation [130] - DT-driven optimization of production lines of pneumatic cylinders [131]
Closed-loop real-time control	- Real-time control of the water pump [133] - Turbine control - Human-robot collaborative assembly system [137] [138] - Application of DT in an additive manufacturing processes [116] - Effective production control of production systems in real time [132]
High-fidelity simulation	- Water pump simulation [133] - Financial and risk simulation - Testing machineries for filling and packaging medications - Simulation of a sheet metal punching machine [139] - cyber–physical system behaviours prediction [115].
3D visualisation	- 3D simulation model that shows cavitation inside a water pump [133] - 3D visualisation of pharmaceutical machines - 3D model of a brake pad wear [140] - 3D visualisation of the punching machine process [139]

4.2.1.2 Dynamic Production Planning and Control (Dynamic PPC)

The traditional view of the German model, which has been consolidated worldwide as the dominant view of the fourth industrial revolution, considers the manufacturing process as the core activity of Industry 4.0. In this sense, the PPC function, which is a central part of a manufacturing system, is responsible for making decisions regarding planning, starting, controlling, monitoring, scheduling, and reprogramming of a production planning, and ensuring the delivery of the products of a manufacturing company. The main activities of a generic PPC are also shown Figure 10.

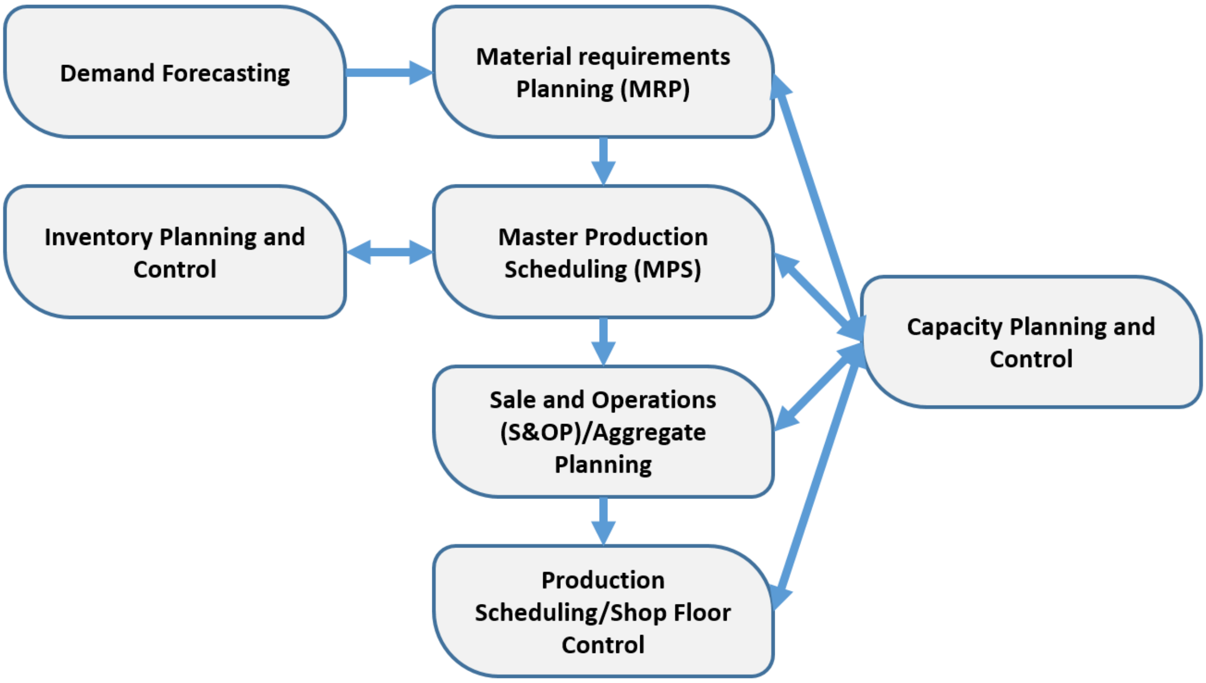

Figure 10: Main Production Planning and Control activities[141]

In recent years, these activities are being supported by novel digital technologies, being more integrated, and automated.

4.2.1.2.1 Demand Forecasting

Forecasting is an indispensable activity in today's production environments. It is widely used in modelling production processes, production planning, and demand forecasting. Demand Forecasting is a field of predictive analytics which tries to understand and predict customer demand to optimize supply decisions by corporate supply chain and business management [141]. It involves quantitative methods such as the use of data, and especially historical sales data, as well as statistical techniques from test markets. Demand forecasting may be used in production planning, inventory management, and at times in assessing future capacity requirements, or in making decisions on whether to enter a new market. Figure 11**Erreur ! Source du renvoi introuvable.** depicts briefly prevalent forecasting models in industrial context [142].

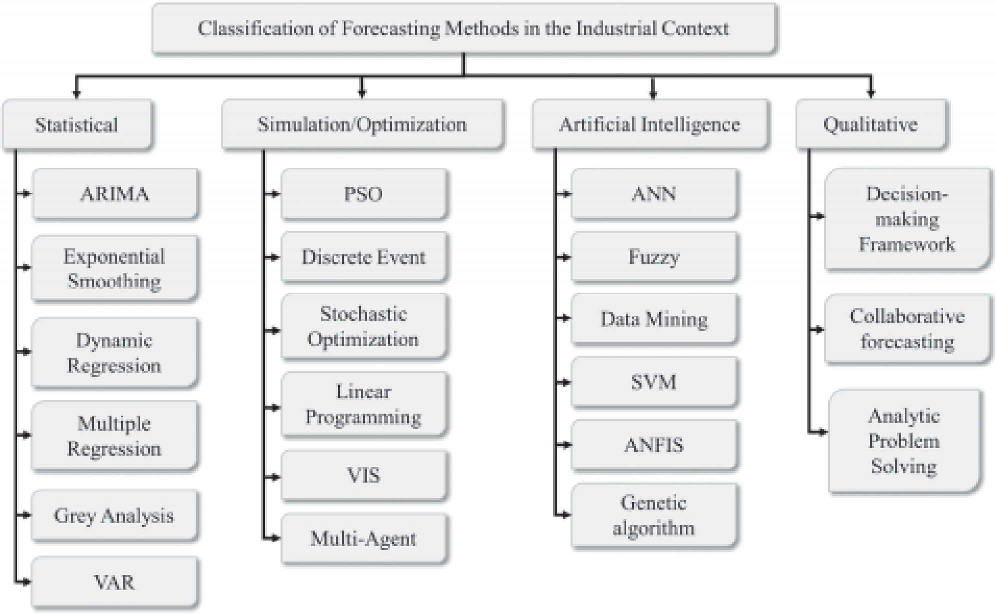

Figure 11: Classification of forecasting methods in the industrial context [142]

In the past, Demand forecasting relied heavily on the intuition and experience of the planner/business. Post-Industry 4.0, it's largely a data-driven practice: by using data from sensors deployed throughout the supply chain.

Developed concepts and applications are based on the IoT, and concern real-time data collection and integration with aggregate planning and inventory management. The forecasting processing and data analytics portion are strongly focused on BDA/AI for supporting smart capabilities concerning the predictability of resources, improving the accuracy and performance of forecasting, processing sets of big data and analytics using machine-learning methods, automatic selection of demand predictors. Other capabilities explored by forecasting include accurate fulfilment of seasonal demands for spare parts [143] based on AM and real-time data collection, and processing for auctions with demand forecasting based on cloud services [144]

4.2.1.2.2 Inventory Planning and Control

Planning and controlling inventories is one of the most complex contexts within supply chain management. According to, inventories also arise from the gap that exists between consumer demand and the production or supply of such products. However, these causes can be mitigated by the following strategies [145]:

- Obtaining accurate and real-time information on demand at the point of consumption. The more information available in a timely manner, the easier and more effective the planning will be.
- Consolidation of distribution centres and warehouses to increase demand volumes per facility, as higher demand volumes generally lead to lower levels of demand variability.
- The standardization of products to avoid the maintenance of inventories of a great diversity of items that only differ in minor aspects of form, color, condition, etc. The final product features can be implemented at the time of receiving orders from customers.
- Improving demand-forecasting systems through widely recognized techniques.
- The improvement of alliances and communication systems with suppliers and customers to reduce delivery times,
- The issuance of joint orders for various groups of items in order to balance their inventory and the consolidation of shipments from or to localities, using facilities such as cross-docking and
- The reduction of delays throughout the supply chain, including transit times in transport systems.

These strategies have been considered in several research works: Real-time monitoring and control with PEID [146], integration between forecasting, customer service, and aggregate planning, smart inventory system concepts (sensor data, analytics, CPS integration, and green attributes) [147], automatic inventory management, continuous monitoring and optimization, IoT-driven-e-Kanban, and smart vendor managed inventory systems. Additional capabilities include flexibility of choice between decentralized and centralized safety inventories, mass customization/direct digital manufacturing for low-volume production, and improvements in the real-time traceability and decentralized control of parts, kits, and available spare parts stocks [141].

4.2.1.2.3 Sale and Operations (S&OP)/Aggregate Planning

For these activities, related practices concern real-time data collection for information sharing and collaboration, aggregate planning based on Cloud Manufacturing, and applying BDA/AI and analytics technologies for enterprise and control systems integration. Aggregate planning is found in searched articles exploring IoT digital capabilities for multi-level data sharing, traceable data flows, and integration with demand forecasting, inventory control, and manufacturing execution system (MES)/ERP systems. In a CMg environment, the S&OP employs real-time integration to feed production planning and control operational tasks and adaptive real-time pricing integrated with sales data, adequate level capacity data, production scheduling, and S&OP desegregation [141]. The smart capabilities explored for BDA/AI include real-time optimization prices combined with big data processing, information cost and inventory level monitoring integrated for S&OP processes, and spare parts demand planning integrated with S&OP.

4.2.1.2.4 Master Production Scheduling (MPS)

IoT and CPS-based Master Production Scheduling is addressed in. IoT supports demand-driven and real-time capabilities for the PPC function, providing synchronization of the IoT with the capacity, scheduling, MPS, and. The CPS support capabilities concerning real-time production scheduling, enterprise, and control systems, with distributed and collaborative decision-making through MES, MPS/ERP, and CPS integration [141,148–150].

4.2.1.2.5 Material requirements Planning (MRP)

For MRP, several works have been performed and adopted at industrial level [141]. Research activities and practices explored the integration of building information models, ERP/MRP systems with resources and data systems, and MRP element digitalization following context-awareness resources [148], real-time resources status monitoring, responsive shop floor material management, automatic data collection from material controls integrated with ordering systems, data-driven simulations to predict material flows and shop floor operations behavior, and real-time sensing and positioning using a data-driven optimization of materials, and intelligent automated guided vehicles. In a CPS environment, the IoT supports capabilities related to extending MRP with real-time calculations, early reports, traceability, and visibility in the food chain [151], in addition to MRP automatic optimization, prediction, and re-scheduling based on the DT model [152]. The AM technology provides smart capabilities, including direct digital manufacturing with minimization of the handling and processing of materials, and minimization of the MRP complexity with a reduction of logistics flow is smart [153].

4.2.1.2.6 Production Scheduling/Shop Floor Control

The production scheduling and shop floor control activities are explored in greater detail for Industry 4.0 in all technologies considered in chapter 3.1.

The leading enhancements are related to digitalization and networking integration in manufacturing execution. These Improvements at the level of manufacturing execution, scheduling, and control include real-time shop floor monitoring, resource traceability, data collection, data mining, and real-time information sharing for collaborative production scheduling [141].

The concept of smart scheduling is based on the integration of digital capabilities for real-time, data-driven, collaborative, green energy-aware, and automatic data collection, and can be used for, e.g., 3D printer scheduling. Additional contributions concentrate on adaptive and distributed shop floor control, integrated scheduling of enterprise and control systems [154], synchronization task scheduling, operations (vertical/horizontal synchronization) for real-time visibility of the shop floor on a mobile display [148], data-driven simulations to predict material flows and shop floor operations behavior [155], flexible and reconfigurable production scheduling [156], responsiveness and real-time optimization. The application of CPS for production scheduling and control are related to smart scheduling and automation. Smart scheduling in the context of CPS is based on the smart capabilities of scalability, modularity, autonomous and decentralized data collection, data-driven operations, adaptiveness, flexibility, and collaboration, for scheduling and shop floor control systems [149]. Other practices concern cooperative cyber-physical production systems integrated with the IoT-MES/APS. Shop floor control predominates the smart capabilities regarding automation, such as autonomous production control and task integration based on CPS/AI, predictive maintenance integrated to production scheduling and based on CPS/AI [79], intelligent planning and control algorithms for optimized and automatic human-robot task allocation, manufacturing cells with autonomy (intelligent perception, optimization/simulation, awareness, prediction, and control), and self-optimization (self-thinking, self-decision-making, self-execution, and self-improvement). Concerning AM, the main contribution explored are direct digital manufacturing, real-time traceability of parts and machines, decentralized control of individual parts and kits, scalability, synchronization operations, planning and control, dynamic order acceptance for on-demand production, optimum allocations of 3D-printers, mass customization control, 3-D printer production, inventory integration, and product model [157], optimization of 3D-printer scheduling, integration of detailed adaptive process planning, and AM production planning and scheduling [158]. In a CMg environment, the main capabilities explored are servitization, production scheduling-as-a-service for manufacturing-as-a-service [141], digitalization of production scheduling via real-time auction and performance analytics, optimization production scheduling, flexibility, and reconfigurable lines based on cloud services [159]. The core smart capabilities based on BDA/AI are real-time MES and object traceability for adaptive and optimized production scheduling, smart scheduling based on big data collection, analysis, and optimization, energy-smart/green optimization, predictability/ event-driven scheduling, and automated data analytics/embedded self-learning/AI [160].

4.2.1.2.7 Capacity Planning and Control

In capacity planning and control, industry 4.0 technologies have been explored and adopted in the digital environment, and support integration of forecasting and inventory activities. The core competences/capabilities explored for capacity management are the digitalization of capacity resources with real-time data collection and monitoring through products with product embedded intelligent devices (PEID) [146], synchronization of a PPC plan module (MPS, MRP, capacity and production scheduling) [148], data-driven-predictive capacity planning [156], and traceability and/or processing of machine and real-time monitoring status products. AI applications in CPS support the integration of control tasks (order releasing, sequencing, and capacity control) and predictive maintenance planning into PPC [79]. CMg and BDA/AI support capabilities such as scalability, reconfiguration, and flexibility in production capacity management, production resource monitoring with information and material flow optimization, integration and synchronization of capacity with other systems and operations, and predictive and robust capacity management. AM has been explored to optimize and manage a distributed, flexible, and available capacity of 3D-printers [141].

4.2.1.3 Decision Support System for continuous production plans evaluation

To compete in a dynamic situation, manufacturers must respond quickly to changes in customer needs by making efficient adaptations to their internal processes, in line with their customer requirements. One important aspect is making the right decision using the right decision support systems (DSS) in a complex environment. There are many different types of DSS. The most common ones are listed in Table 6.

Table 6: Decision Support Systems Types [161]

DSS Type	Description
Data Driven	They have file drawer, data analysis and analysis information systems. They facilitate Data Warehouse, access and retrieval from large data bases of structured data

Model Driven	An underling model that incorporates various disciplines such as: accounting, financial, representation, optimisation etc. Model Driven DSS manipulate models instead of data in the analysis and the decision-making process. There is no need for large data bases.
Knowledge Driven	Provide suggestion and recommendations to users for certain problems. They also are called management expert systems or intelligent decision support systems. Problem solving is their main focus and they exploit data mining techniques, such as browsing big data for relationship in the content of the data.
Document Driven	Retrieval of unstructured documents and web pages with storage and processing technologies for document retrieval and analysis. Documents are: company policies, catalogues, meeting minutes, records, historical documents etc.
Communication Driven	They are also called GDSS (Group Decision Support Systems). Their first purpose is to facilitate the communication between the members of a group in the decision-making process. They support scheduling, document sharing, bulletin boards, electronic communication etc. They are almost always used as project management tools.
Hybrid Systems	Hybrid DSS are composed by diverse types of DSS. There are Web -based DSS that include communication, data and knowledge driven systems. OLAP is a software category with many possible views of information
Intelligent	The latest development of DSS. They combine three several types of DSS into one: - Passive DSS. The classical Data Driven with extensive access to large data bases and rule engine - Active DSS, which provide personalised decision-making process depending on learning processes. Knowledge-Based Systems (KBS) is one of the Active DSS. - Proactive DSS, are also known as Ubiquitous Computing Technology-based DSS (ubiDSS) and are divided to pull-based proactive, push-based proactive and push-based automated applications.

The most common DSS application are implemented in production lines, weather forecasting, health care organisations, financial and stock market analysis. Also, air traffic control, advance traffic control centres, as well as manufacturing decisions are based on DSS and their suggestions. Oil refinement manufacturing, maintenance decision – making processes are mostly based on DSS. Large shop floors with many assets are inclined to use DSS instead of Computerised Maintenance Management System (CMMS), because CMMS can be absorbed in the DSS. The need to develop smart factories and solve many maintenance, production and safety problem in manufacturing environments drive the research about DSS. Decision – making processes concerning the above factors improve shop floor organisation and maximise benefits while minimising the costs and problems which often happen on shop floors.

The intelligent techniques used in the most recent research studies and adopted in manufacturing environments are: Data Mining and ANN, Temporal Difference (TD) Learning methods, Genetic Algorithms and Fuzzy Logic. Also, Gaussian Dispersion Model, Mobile Agents and Multi – Agent Systems, as well as the DSS types described in previous chapters are part of the research areas.

The target of a decision support system is to propose the most favourable alternative under the given situation. Optimization models integrated into a DSS have been developed in many environments. Especially in production & operations management and supply chain management the area of optimization models has become an important field for DSS. Various decision support models are available for different levels of the supply chain, including production planning and scheduling, demand management, and logistics planning. Model-driven DSS using simulation and rapid modelling techniques conduct multiple experiments to show the effects of alternative conditions and courses of action. For decision support in the area of supply chain management several kinds of simulation methods are in common use, e.g. Monte Carlo simulation, discrete simulation, agent-based and multi-agent simulation, system dynamics, and visual simulation [162]. Table 7 lists a set of DSS applications in different environments.

Table 7: Example of DSS application for planning and scheduling

Year	Contribution	Field Type	Topic		Type	Case Study
			Planning	Scheduling		
2013	Developing a web-based DSS	Agricultural		*	Model Driven	Australian farms
2013	Developing a service-oriented DSS based on ERP approach	Industrial	*	*	Model Driven	Automotive manufacturer in Iran
2013	Developing a hydraulic model based emergency scheduling DSS	Water	*	*	Knowledge Driven	Raw water supply in China
2013	Using principal component analysis and logistic regression to develop a scheduling DSS	Industrial	*	*	Communication Driven	An automotive manufacturer in Iran
2013	Applying DMAIC cycle to develop a DSS	Academia		*	Communication Driven	An academic institution in India
2013	Developing a DSS based on the goal integer programming	Cruise Industry		*	Data-Driven	Cruise line
2013	Presenting an approach for scheduling multiple projects with competing objectives	Industrial		*	Communication Driven	Electric utility company in Midwest USA
2014	Implementing a web-based DSS to reduce the scheduling complexity	Service Sector		*	Communication Driven	Letter shop company
2014	Developing a DSS to simultaneously implement supply network configuration and schedule the operations of a company	Industrial	*	*	Data-Driven	A milling machines manufacturer in Europe
2014	Developing a mathematical model-based DSS to facilitate resource scheduling for activities	Oil & Gas	*	*	Data-Driven	Offshore wells in Brazil
2014	Developing a bi-objective vehicle routing and scheduling optimization problem	Transportation	*	*	Communication Driven	Distribution of LPG in Osaka, Japan
2014	Developing a DSS using heuristics to reduce scheduling time	Air Force		*	Communication Driven	Fighter squadrons in Turkey
2015	Developing an RFID-based DSS for scheduling the distributed manufacturing environments	Industrial		*	Model Driven	Clothing manufacturer
2015	Interdisciplinary design of a scheduling DSS for SMEs	Industrial		*	Communication Driven	Food product manufacturer
2015	Developing a DSS to improve the operational and making near-optimal decision under system constraints	Energy	*	*	Model Driven	Power Plant in India

2015	Proposing a DSS based on decision rules dealing with stochastic and dynamic demand	Transportation		*	Model Driven	N/A
2015	Developing a DSS for industrial applications	Pulp & Paper	*	*	Data-Driven	Paper manufacturer
2015	Embedding optimization procedures to schedule surgery operations	Heath	*	*	Communication Driven	Hospital in Spain
2015	Developing a mixed-integer, linear program based DSS	Maritime		*	Communication Driven	Search and rescue
2015	Developing a mixed-integer programming model to support driver scheduling problems	Transportation		*	Knowledge Driven	A regional truckload carrier in Mississippi
2015	Development of an expert system to support energy-efficiency in the compound feed production	Compound feed Production	*	*	Knowledge Driven	A Compound feed manufacturer in north Germany
2019	Artificial intelligence supported platform for the assistance of production control for improving energy efficiency	Waste recycling, Food Processing	*	*	Knowledge Driven	Food Manufacturer and Recycling Stations in Germany

4.2.1.4 Data analytics for business intelligence and value creation out of production data

The main goal of Data Analytic and Business Intelligence and is to increase the quality of the information that is available for decision making induced by the improvement of data processing. This combination has significant contribution in improving the production development [163]. Insights derived from data analytics can enhance productivity and competitiveness, boost innovation and growth as well as generate new manners of competition and value capture across organizations [164]. The prevalent use of data ensures transparency, aids the discovery of market needs, uncovers processor service variability, improves performance and assists in the adoption of more sustainable practices. In the specific case of the manufacturing sector, five main areas in which Data analytics contributes to business intelligence and value creation are identified and summarized in Figure 12 [165].

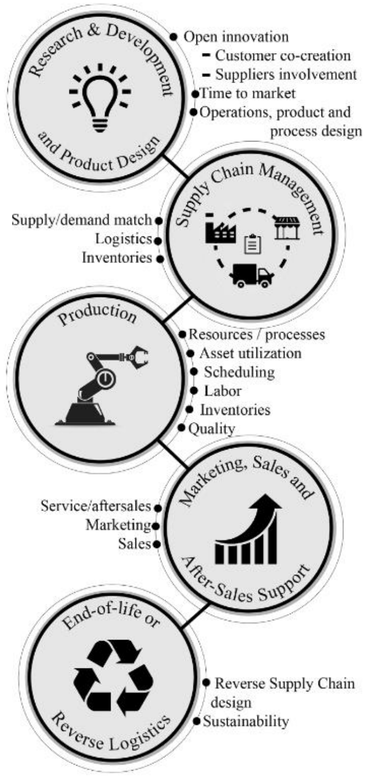

Figure 12. The manufacturing domains benefiting from data analytic [165]

Examples:

- Production: There are a number of successful applications of data analytics in the domain of production. Some examples include resources (such as energy and water) and processes, tooling optimization, asset utilization, quality, inventories, labour, among others.
- Rolls-Royce product oriented product-service system: With the advent of new technologies such as the IoT and big data analytics, the development of after-sales services has been facilitated by incorporating sensors on products that inform the manufacturer about performance, defects and usage patterns

while in hands of the customer. This translates into a business model shift in which the manufacturing company transitions from "doer" to "problem solver". An illustrating example is that of Rolls-Royce aerospace engines business unit whose business model changed from merely selling engines to "power-by-the-hour". As part of this offering, customers pay an hourly fee for the power generated by the engine and receive continuous support and maintenance from Rolls-Royce to ensure their correct functioning. A challenge associated with these types of offerings is that of defining appropriate data access rights and privacy since manufacturers' oversight of usage patterns may not be always welcomed by the average customer. An illustrating example is that of Rolls-Royce aerospace engines business unit whose business model changed from merely selling engines to "power-by-the-hour". As part of this offering, customers pay an hourly fee for the power generated by the engine and receive continuous support and maintenance from Rolls-Royce to ensure their correct functioning.

- Dynamic pricing: A common practice, originally introduced in industries where the short-term capacity (supply) is difficult to change, such as airlines, hotels and sporting events, is the use of dynamic pricing where the price of an item varies in real-time to account for fluctuations in market conditions such as demand, inventory levels, competitor offerings and customer history. The adoption of dynamic pricing strategies has proliferated due to an increased availability of demand data, the emergence of new technologies that facilitate changing prices, and the availability of software for analysing demand data and for dynamic pricing. These new technologies allow retailers and manufacturers to combine information about sales with demographic data and customer preferences, and to use it to optimize pricing and markdowns as well as to evaluate the effect of promotions.
- Safety stock optimization in Procter & Gamble: This real application of BA concerns Procter & Gamble, where optimization was conducted locally using spreadsheet-based models at each stage of the supply chain followed by a multi-echelon optimization The model used for the latter was trained using multiple variables. For example, not only actual past demand was utilized but also the forecasted shipments for the previous thirteen weeks as well as those for the coming thirteen weeks. Other variables included materials lead times, production times, review periods, time for transportation and movement, quality assurance duration and cost variability at each location.

4.2.2 Application of Industry 4.0 technologies: examples

The literature provides several contributions related to the application of Industry 4.0 in production engineering.

Miranda et al. (2019) focus on the topic of smart product development according to a reference framework based on the adoption of CPS to create sensing, smart and sustainable products. Tao and Qi (2019) develop a Service-oriented Smart Network (SoSM), in which the IoT is used to connect all the users involved in the design phase of formalising the product information model. The specific receiver and feedback mechanism enabled by the IoT improves the effectiveness of data source collection in product development [166]. Bressanelli et al. (2018) stress the capacity of the IoT and BDA in improving product design from a Circular Economy (CE) perspective [167]. Indeed, the IoT allows data to be collected directly from the product in order to identify potential improvements in the design phase, which can be very useful when a new version of the physical product is to be launched. In addition to collection, these data also have to be processed to underline any improvement trends.

Some works in the literature demonstrate the usefulness of BDA technology in data processing. Operational big data collected from sensors has a positive impact on product design in CAD systems. Indeed, BDA is a lever for customized design, since more and more active or passive information on user behaviours are exposed to the internet [90,97], so designers can exploit these data to acquire information about potential design features and improvements in order to satisfy latent customer needs. This is further confirmed by [166] who state that BDA can help designers to transform data into enlightening knowledge. Moreover, [93]state that, combined with ML, information collected from product lifecycle can be used to optimize product design [93].

Product development is also supported by the use of Cloud technology, which provides an environment where data and functionalities are deployed; specific customer requirements across the global network can be transmitted to the Cloud for storage, computing and analysis, promoting distributed and collaborative product design [93,104].
Automated simulation can support and accelerate virtual prototyping [93], while simulation is useful in technical assessment before the prototyping stage [168]. As mentioned in Section 4.2.1 DT is also important in product development as it replicates the digital representation of physical products for iterative optimization of personalized design.
Visualization technology, for example Augmented Reality (AR), can also support the product development process as it provides a concrete vision of the end product for assessing, in particular, the aesthetic details [169].
The development of new products can be enhanced by use of AM. On the one hand, AM allows designers to achieve products featuring complex shapes that would not be feasible with traditional production techniques. On the other hand, this production technology, characterized by reduced production lead time, guarantees rapid prototyping and obtains the product components quickly for subsequent testing [170,171]. For demand forecasting, developed concepts are based on the IoT, and concern real-time data collection and integration with aggregate planning and inventory management [172]. The forecasting processing and data analytics portion are strongly focused on BDA/AI for supporting smart capabilities concerning the predictability of resources, improving the accuracy and performance of forecasting, processing sets of big data and analytics using machine learning methods, automatic selection of demand predictors, real-time data collection, and monitoring and diagnosis with data analytics tools for the integration of demand forecasting with capacity and inventory management [173]. Other capabilities explored by forecasting include accurate fulfilment of seasonal demands for spare parts [143] based on AM and real-time data collection, and processing for auctions with demand forecasting based on cloud services [144].

ACROBA – AI-Driven Cognitive Robotic Platform for Agile Production environments (H2020 funded research project, https://acrobaproject.eu/). ACROBA project aims to develop and demonstrate a novel concept of cognitive robotic platforms based on a modular approach able to be smoothly adapted to virtually any industrial scenario applying agile manufacturing principles. The novel industrial platform will be based on the concept of plug-and-produce, featuring a modular and scalable architecture which will allow the connection of robotic systems with enhanced cognitive capabilities to deal with cyber-physical systems (CPS) in fast-changing production environments. ACROBA Platform will take advantage of artificial intelligence and cognitive modules to meet personalisation requirements and enhance mass product customisation through advanced robotic systems capable of self-adapting to the different production needs. A novel ecosystem will be built as a result of this project, enabling the fast and economic deployment of advanced robotic solutions in agile manufacturing industrial lines, especially industrial SMEs. The characteristics of the ACROBA platform will allow its cost-effective integration and smooth adoption by diverse industrial scenarios to realise their true industrialisation within agile production environments. The platform will

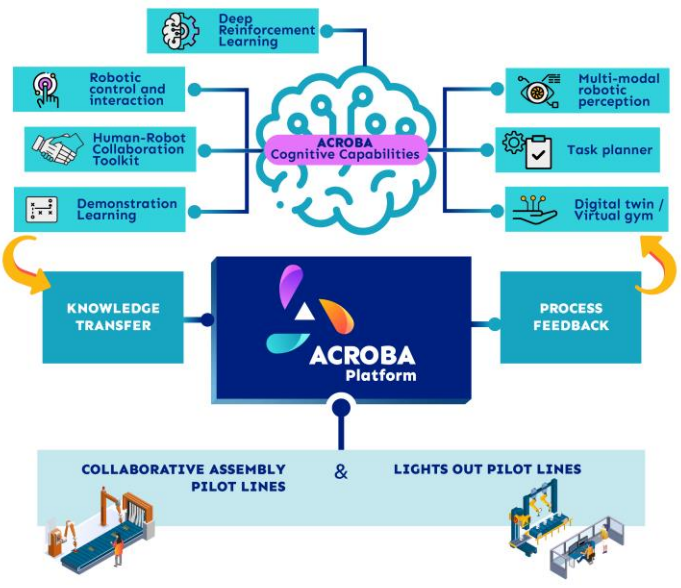

Figure 13: Concept of R&D project ACROBA. Source: ACROBA Project

depart from the COPRA-AP reference architecture for the design of a novel generic module-based platform easily configurable and adaptable to virtually any manufacturing line. This platform will be provided with a decentralized ROS node-based structure to enhance its modularity. ACROBA Platform will definitely serve as a cost-effective solution for a wide range of industrial sectors, both inside the consortium as well as additional industrial sectors that will be addressed in the future. The Project approach will be demonstrated by means of five industrial large-scale real pilots, Additionally, the Platform will be tested through twelve dedicated hackathons and two Open calls for technology transfer experiments.

INSERT - AI-based assistance system for concept planning in production and logistics (German funded research project). Intense global competition, shorter product life cycles, and an increasing number of variants require flexible and adaptable, but also economical production and logistics systems. The time-intensive planning process shall be significantly shortened by an assistance system to become faster and more cost-efficient. In the project "INSERT", a prototype of an AI-based assistance system for concept development for logistics and production planning is being developed. This assistance system supports the entire planning process and provides a platform for the development of logistics and production concepts.

Binntelligent - Intelligent Information Technologies for Process Optimization and Automation in Inland Ports Hide project description (German funded research project). In Binntelligent, digital services as well as intelligent processes, procedures and information technologies for the optimization of trimodal logistics and transhipment processes in inland ports and the improved collaboration between inland and seaports are designed, implemented and evaluated in the field of application. It creates a cross-company visibility and transparency of decision-relevant information that allows predicting events in the supply chain. For this purpose, an information system for (semi-) automated information distribution, operative process support and predictions will be developed. In addition to event predictions, forecasting capability in inland ports is achieved by simulation-based optimization of trimodal transhipment, which processes real-time real data and enables adaptability in synchro-modal freight traffic. Binntelligent considers logistics processes for containers and bulk goods in inland ports as well as the pre- and post-carriages. The planned technologies are designed for use in the Weser and Mittelland Canal shipping areas with the ports of Hanover, Braunschweig, Bremen and Bremerhaven and will subsequently be implemented for application-oriented testing and evaluation.

AdaptiveSBO - An adaptive simulation-based optimisation approach for the scheduling and control of dynamic manufacturing systems (German funded research project). The planning and control of production processes has a significant influence on the performance of a job shop manufacturing system. The production is subject to dynamic influences (e.g. faults caused by machine failures or rush orders), which have to be considered for the production planning and control. Common methods are

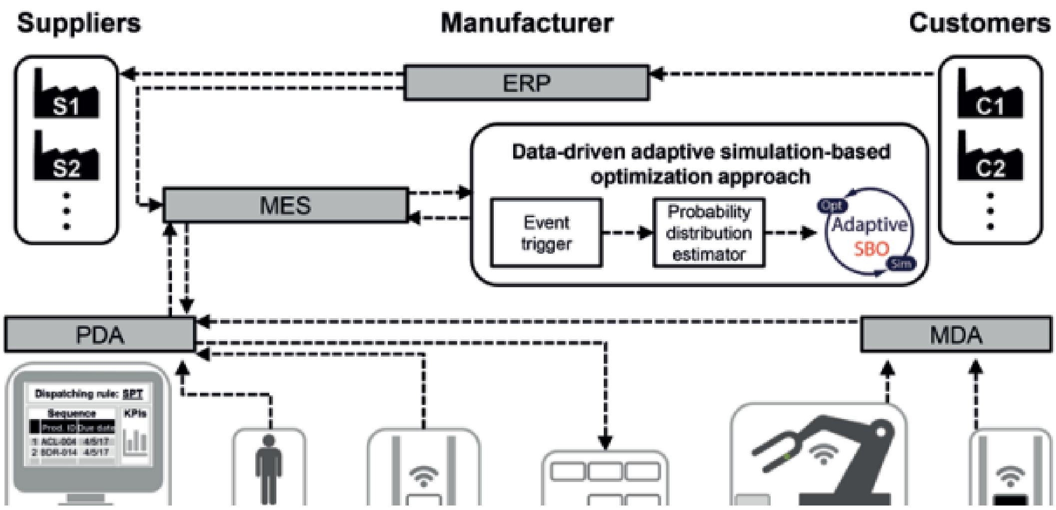

Figure 14: AdaptiveSBO - Data Exchange Framework

therefore normally divided into modules for calculating plans and modules for operational control. In general, optimisation only takes place at the strategic planning level, while detailed planning is carried out on the basis of simple, static dispatching rules. This allows the generation of schedules in short computation times, but generally no optimal schedules based on the current state of the production system are generated. In the first phase of the Brazilian-German cooperation project, a simulation-based optimisation method for controlling dynamic job shop production has been developed. The classical approach of simulation-based optimisation was extended in such a way that the dynamics of job shop manufacturing are taken into account and the optimisation of planning decisions and control rules is always based on the current system state. The developed method was evaluated considering the job shop production of a Brazilian producer of mechanical parts.

In the second project phase, a method for the integrated control of inventory, production and maintenance processes has to be developed in order to map the current status of a production system in more detail. This means that maintenance orders can be scheduled for the machines in addition to the existing method and the inventory stocks can be taken into account for planning and control. Approach Initially, methods for planning maintenance jobs (Germany) and methods for inventory control (Brazil) using up-to-date system data will be developed in parallel. Subsequently, both approaches will be combined to an integrated inventory, production and maintenance control method, which will then be evaluated in a real scenario using data from the industry partner Rudolph Usinados as well as by scenarios from the literature.

DIH4CPS - Fostering DIHs for Embedding Interoperability in Cyber-Physical Systems of European SMEs (H2020 funded research project, https://dih4cps.eu/). The initiative for Fostering DIHs for Embedding Interoperability in Cyber-Physical Systems of European SMEs (DIH4CPS) will help European enterprises overcome innovation hurdles and establish Europe as a world leading innovator of the Fourth Industrial Revolution. DIH4CPS will create an embracing, interdisciplinary network of DIHs and solution providers, focussed on cyber-physical and embedded systems, interweaving knowledge and technologies from different domains, and connecting regional clusters with the pan-European expert pool of DIHs.

QualifyAR - Development of an AR framework with extended sensor technology to support training and education in the aviation industry (H2020 funded research project). The complexity of the tasks of technical professions in the aviation industry is high. Research is therefore being conducted into new approaches to knowledge transfer for both training and continuing education. The QualifyAR research project aims to support the training of apprentices in aircraft construction. Especially in aircraft construction, the highest demands are placed on training. Accordingly, the use of digital and individual learning environments is being pursued with emphasis in order to improve learning success on the one hand and to prepare the later use of digital assistance systems in the productive process on the other. The QualifyAR project is dedicated to the development of an AR-based qualification system with integrated process step recognition and automated quality control. By means of an AR-framework and on the basis of predefined process databases, teachers should be able to digitally map even complex teaching tasks and to tailor them, taking into account the individual technology-portfolio. Information and insights of the system are transmitted to the student via a human-system interface using AR-projection in a context-sensitive way. In this project BIBA is researching image-based process step recognition and the use of an IoT construction kit with a focus on signal processing, in order to be able to assess the quality of the task execution on the basis of 2D/3D image data as well as 1D process data, such as torques of cordless screwdrivers, by means of artificial intelligence.

Worksuit 4.0 - AI-based Toolkit for enhancing Human-Robot Interaction in Industry 4.0 (EIT-H2020 funded research project, https://www.worksuit40.eu/). An EIT-Manufacturing project that aims to bring a functional toolkit to market consisting of a wearable fibre-optic sensing system for 3D-human motion capturing in combination with advanced activity and process mining capabilities. As enabling technologies, the toolkit hardware and software components will provide the means for offering safer human-machine interaction, while maintaining enhanced collaboration levels. Moreover, the appliance of fundamental ergonomic principles (e.g. body postures) is pursued during the execution of process-related tasks, through real-time activity recognition and classification mechanisms. The outcome of Worksuit 4.0 will be the key-driver for providing a wider spectrum of sophisticated safety and context-oriented applications in assembly processes and supporting continuous process control and optimization of Human-Robot Collaboration (HRC) workplaces.

ecoKI - Development of a research and technology platform for increasing energy efficiency through AI technologies (German funded research project). Due to the fact that there is still a lack of systematic solutions for SMEs that provide robustness and applicability of AI and take into account the restrictions of software and infrastructure in SMEs, the overall aim of the ecoKI project is to support SMEs by developing an infrastructure for increasing energy efficiency through AI technologies. ecoKI contributes to making digitization and AI modules(solutions) more generic in the area of energy efficiency and enhance/reduce the barriers of their adoption (easy as possible to use) at industrial level.

KIPro - AI supported platform for the assistance of production control for improving energy efficiency (German funded research project). KIPro examined the possibilities of improving energy efficiency in industrial plants with strongly varying properties of the input materials. The aim is to reduce energy demand through the use of methods of artificial intelligence, such as artificial neural networks in combination with deep learning, architectures, semantic mediators and expert systems, without compromising product quality. These systems analyse large amounts of data and identify specific patterns and rules, training and improving their own knowledge base in order to offer specific proposals for an energy-optimized process. An example within KIPro represents the development of a material and volume flow detection. Thereby, different sensor data is combined and analysed for the detecting different materials under application of deep learning.

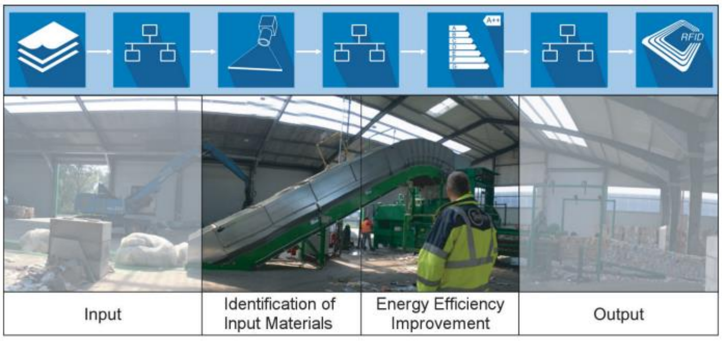

Figure 15. KIPro vision

PrintAI - Self-learning software platform for 3D-printer farms for individualized mass production using the examples of shoes (German funded research project). The use of 3D printers has been established as a recognized manufacturing process in recent years. In addition to rapid prototyping, the economical production of small series even of quantity 1 and the spatial decoupling of development and production/distribution are decisive advantages of this process. In addition to a large number of different product types, 3D printing also offers the possibility of printing highly individualized shoes in one piece. By creating printer farms that require only a small amount of space and installation effort, decentralized production/distribution sites can be created almost anywhere. In order for these to work optimally, it is necessary to develop largely automated quality control loops that support the operators in detecting and avoiding misprints.

PassForM - Resource-based process management through flexible use of intelligent modules in hybrid assembly (German funded research project, https://passform.biba.uni-bremen.de/). The project creates a modularly reconfigurable assembly station. It allows for a more flexible design of manual and hybrid assembly stations and systematic automation, which improves scalability, re-usability and responsiveness to market developments. Bidirectional information and control instruction exchange enable and ease the integration of the modular assembly stations into existing assembly organizations. For this purpose, a material supply module, a conveyor module and a robot module are implemented. The goal is to unite the opposing requirements of productivity and flexibility in the assembly area of medium quantities. The project will fill the gap between manual and highly automated processes. The performance of the modular, hybrid assembly system will be evaluated and based on application scenarios in variant assembly groups.

EKiMuPP - Design of a digital and AI-assisted flexible assembly line to increase product and process innovation (German funded research project).. In order to deal with the shorter innovation cycles at product and process level in assembly, assembly systems must be enabled to react swiftly to an increasing number of variants and changed framework conditions. These conditions include, in particular, new product requirements and high volatility in terms of sales volumes. Economical operation and control of complexity are thus only possible with new, innovative concepts. Furthermore, assembly can serve as an innovation driver for both products and processes through the implementation of new technologies. The objective of the project is to develop a new, flexible assembly line to increase product and process innovation in emerging and fast growing companies. The cooperation of employees along the entire process chain will be increased and optimized by digital interaction possibilities. In addition, the training and support of operational employees will be actively supported. Thus, on the one hand, the adaptability of the assembly line will be increased and, on the other, the innovative drive of the entire company will be supported. In order to establish assembly as an innovation driver for young companies and to strengthen the innovation level of products and processes, new technologies are being developed as well as their interaction will be considered in the research project. The foundation is a versatile assembly system, which serves as an integrator for new technologies. With the use of the digital assistance system, training times are shortened, and process orientation is improved. In addition, digital knowledge management enables multimodal communication between operational and planning personnel. Variant management supported by artificial intelligence will firstly enable rapid scaling and secondly control increasing complexity by increasing the number of product variants. The overall system is to be developed in a modular fashion and its benefits demonstrated and evaluated in practice. For this purpose, typical products for manual assembly will be selected and the overall system will be evaluated in the company context. In addition, the functionalities of the overall system will be evaluated in a practical test with further product variants in order to demonstrate its product-independent applicability.

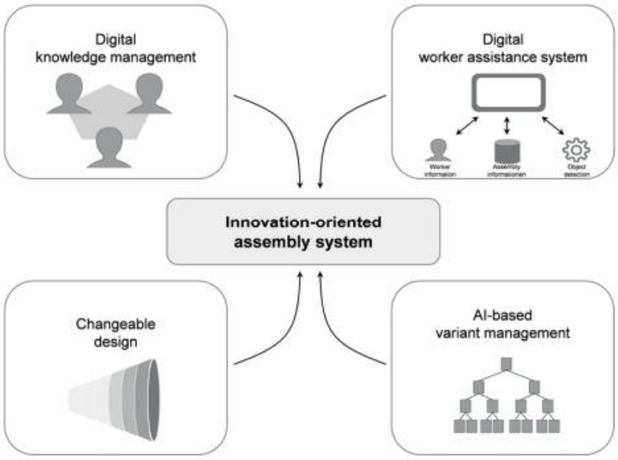

Figure 16: Concept of the R&D project EKiMuPP

KIPro – AI-based assistance system platform for complex production processes in mechanical and plant engineering (German funded research project). The operation and configuration of woodworking machines has always been a challenge, especially due to the high proportion of manual production steps. This situation is currently exacerbated by the increase in product variants and more complex logistics chains. AI-based assistance systems and machine learning offer a way out. These approaches make it possible to offer user-specific support, to adapt system configurations automatically and to detect errors at an early stage. The assistance system platform supports the entire work process at individual production workstations as required. In addition, the platform enables the implementation of flexible production approaches via an intelligent control system, so that the employees can be deployed flexibly according to their skills and the workload. The project aims to pursue the target parameters productivity while taking into account the skills of the employees. For example, as part of the planning of new assembly tasks, the assistance system indicates which tools and consumables are required on site based on the product, resource and process models. When carrying out the assembly task, the employee receives information on the correct assembly of the units or machines. While inexperienced employees can request step-by-step instructions, experienced employees receive support according to their requirements. On the basis of individual behaviour, the AI is used to predict the extent to which the employee needs informational support in a certain assembly step or in a certain situation. In principle, the software works on the principle that users always control the cognitive assistance system. For example, you can request additional information on the current assembly step or generally change the scope of support via your user profile. In addition, the software also supports the communication between design, industrial engineering and assembly, for example to be able to quickly address assembly-related problems. Furthermore, the technical documentation takes place via the assistance system, so that proof of proper assembly can be provided at any time. At the same time, the software should enable the implementation of intelligent and flexible process planning models in order, for example, to avoid waiting times at individual workstations and to be able to deploy employees optimally according to their qualifications.

KIAAA – An AI assistant for training in automation (German funded research project).. Automation is a main driver of current technological leaps, examples are increasing automation (Industry 4.0) or increasing use of data. However, the training of automation experts is a challenge due to the interdisciplinary: automation specialists must have knowledge of information technology, electrical engineering and process and manufacturing technology. This challenge manifests itself particularly in large training groups, since individually adapted assessments of learning outcomes are hardly possible. In this research project, training and education software is to be created that actively supports automation experts in their learning through individualized and immediate feedback. The basis for this is an adaptive simulation of typical production processes and automation systems. Using artificial intelligence (AI) and machine learning (ML), a trainer agent analyses the automation company's level of knowledge and develops a sequence of learning scenarios. In addition, a role model agent offers help in the form of automation solutions, i.e. it generates sample solutions as models for the automation company. In addition to the AI-based role model agent, automation engineers can also benefit from solutions from other learners in a collaboration environment and exchange solutions and knowledge. The training and education software should be available to the general public.

EKI – Engineering for AI-based Automation in Virtual and Real Production Environments (German funded research project). Both end customers and industry need new products and product variants at ever shorter intervals. Manufacturers are not only faced with such time-to-market requirements, but are also under constant pressure to increase productivity, save resources and reduce costs. All of this has led to a strong need for new adaptive and changeable systems and in particular for corresponding automation solutions. Engineering in particular, i.e. the adaptation of the automation solution by experts, has proven to be a bottleneck, which is why engineering environments for automation solutions have to be reinvented. Currently, AI and especially machine learning (ML) are creating completely new approaches to automation, especially for adaptive, i.e. changeable systems (e.g. for new product variants). These AI approaches automatically allow the production sequence, i.e. to create the automation strategy or to adapt it to new requirements - instead of the previous laborious manual work. Other AI components such as predictive maintenance or energy analyses use machine learning to monitor systems. While such approaches to adaptive production have been called for on the European agenda for years, only a few individual aspects such as system modularization, software and mechatronic components or parameter optimization have been examined so far. No general solution has yet been developed for the core problem. This is mainly due to the problem of the lack of engineering methods. From the user's point of view, the engineering approaches for such adaptive systems are a key challenge: On the one hand, it is about being able to react faster to new requirements than before. On the other hand, ML and AI algorithms will also be permanently available as software components. However, such software components have to be put together in an engineering environment by integrators and machine builders (i.e. by people not from the AI area) to form overall solutions. I.e. The core problem is not the algorithmic creation of such KI / ML components but the engineering environment. Corresponding engineering approaches do not exist today. As a solution, a new, open engineering approach with open interfaces is being developed in this project, which enables the integration of ML and KI-SW components into the engineering. A key idea are assistance functions to support plant operators in quickly creating new automation solutions.

Time4CPS - A Software Framework for the analysis of time dependent behaviour in production and logistic processes (German funded research project, https://www.hsu-hh.de/imb/en/projects/time4cps). The use of artificial intelligence has recently been a major driver of

innovation within production and logistic processes. Due to this, many methods exist that can be used to analyse process data. However, in practice many of these projects fail, since an elemental information in production and logistic processes – time – is not being considered.
This is despite the fact, that time dependent behaviour can show many effects and interdependencies and is usually available without the use of additional sensors. So why is the freely available and invisible sensor time so neglected in the domain of optimization?
The main reason is that durations of time can only be measured between two distinct events – which are usually not defined in production and logistic systems. Measurable events do exist (for example in control signals or state changes of discrete sensors), but usually the events relevant to optimization are hidden in continuous, interdependent and high-dimensional sensor values over time. They are therefore unknown and not explicitly usable for optimization algorithms.
The project Time4CPS therefore aims towards the development of a methodology and a software platform to automatically discretize relevant events from production and logistic processes. These can then be used for system monitoring and optimization.
Manufaktur 4.0 - Quality-oriented production control and optimization in food production (German funded research project). The project develops a digitalised, quality-based production planning and control system for food production. The system focus on an optimal use of raw materials (e.g. reduction of the storage time of sensitive raw materials). The development should lead to a better operating grade of the production facilities and an optimization of their energy consumption as well as to an optimized bin management and especially to an increase of the product quality (taste). In order to achieve the objectives, raw material-specific quality-time profiles will be analysed and integrated in an IT-based procedure for quality-oriented production planning and control, which will be implemented as a prototype by the project partner.
DigiWood - Development of a software platform for woodworking machines for the digitization of woodworking processes (German funded research project, https://www.hsu-hh.de/imb/en/projects/digiwood-development-of-a-software-platform-for-woodworking-machines-for-the-digitization-of-woodworking-processes). The aim of the project is to develop an innovative software solution for implementation in new woodworking machines, for automated control, networking and predictive maintenance of new woodworking machines. This software solution is intended to connect the office administration of the woodworking industry with the woodworking machines within the company. Work processes can be optimized in terms of time due to automated parameterization and machine settings, digitization of the automation of work steps between different machines guaranteed, networked production using plug & produce and predictive maintenance of machines and tools made possible on the customer side. Which existing problem is being solved? Current lack of intelligent machine management systems causes delays, quality fluctuations, excessive tool wear and material waste in production, and thus leads to inefficiencies and low production efficiency. The lack of standardized communication interfaces between the machines, as well as the machine and management software, have so far not allowed automated, self-controlling production chains and are the cause of the current manual programming. The new software should make it possible to control woodworking machines automatically via Plug & Produce, to record data in real time and to plan, regulate and control entire production lines independently on the basis of these manufacturing processes. For this purpose, a cloud-based solution is sought through which recipes for manufacturing process control and module linking can be downloaded.
LaiLa – laboratory for intelligent lightweight construction (German funded research project, https://www.hsu-hh.de/laft/en/laila-laboratory-for-intelligent-lightweight-production). The production environment in fiber composite lightweight construction is characterized by a high proportion of manual activities and, at the same time, a high number of variants with the highest quality standards. In aircraft construction, for example, a 100% test of all components is carried out, whereby this activity is mainly carried out manually and the documentation is stored in paper form. As a result, this environment demands a high level of expert knowledge and is heavily dependent on the individual availability of staff. On the other hand, quality-relevant processes are not available digitally, which in later life cycle phases, e.g. in the context of production or in operation, leads to considerable

additional expenditure. At the same time, recurring efforts in the development and integration of solutions inhibit the comprehensive implementation of information and automation technology. As a result, modern data analysis and process optimization cannot be carried out. A major challenge for the introduction of digital technologies is the transfer and further development of research results for use in production.

Various applications of sub-symbolic artificial intelligence (AI), including for the analysis of product quality, system diagnosis and predictive maintenance. Machine learning (ML) models, for example neural networks, cannot be used directly in production, but require a lot of effort, for example for setting parameters. In the field of symbolic AI, there are approaches to formal information modelling to describe machine functions and to ensure semantic interoperability between cyber-physical systems. However, the two areas of AI are usually considered separately in automation technology. The combination of formal knowledge models with approaches from ML has great potential, because machine-readable information can reduce the training effort in the field of ML. In addition, the content of knowledge models can be optimized with “learned” content. This project therefore aims to link symbolic and sub-symbolic methods of AI so that expert knowledge and machine functions are described in a machine-readable manner and methods of sub-symbolic AI are made accessible.

4.2.3 Required capabilities

Table 8: Concepts and corresponding requirements and needs for Production 4.0

<table>
<tr><th>Production Concepts</th><th>Production Concept's Requirements</th><th colspan="2">Expected Capabilities</th></tr>
<tr><td>Digital Twin for machine life-cycle Improvement</td><td>Understand machine specification, Use of modelling and simulation tools, Interconnection of systems (Machines/PLC/Sensors/software applications)</td><td rowspan="5">• Digitalization
• Networking integration in manufacturing execution
• Industrial automation
• Requirement Engineering and Modelling
• Mechatronics
• Prototyping
• Product Design and development
• Virtual commissioning
• Real-time shop floor monitoring
• Real-time resource traceability
• Production Planning
• Production control strategies and techniques
• Event-driven, collaborative, synchronized, smart, flexible, reconfigurable scheduling
• Process mining techniques
• Scalability, flexibility
• Energy efficiency
• Sustainability
• Human-machine and machine-machine interaction techniques
• Performance analytics</td><td rowspan="5">• Collaborative, green energy-aware, automatic data/Information/knowledge management
• ICT protocols and standards
• Data-driven simulations for material flows prediction
• Decision-making Systems, Prognosis, Diagnosis, Cognition and intelligent perception
• Self-thinking, self-learning, self-decision-making, self-execution, and self-improvement
• Mass customization
• Norms/Regulations/Specifications
• Interoperability and system Integration
• Software development of industrial applications
• Visualisation, Virtualisation
• Servitization (e.g. production scheduling-as-a-service)
• Safety and IT-Security
• Project management</td></tr>
<tr><td>Digital Twin for Cyber-Physical Production System Design</td><td>Use and selection of appropriate design technique and product development models, perform virtual commissioning</td></tr>
<tr><td>Dynamic Production Planning</td><td>Use of production planning methods and tools, software development of industrial applications, visualisation</td></tr>
<tr><td>Decision Support System for continuous production plans evaluation</td><td>familiar with requirements engineering, Expert Systems, artificial intelligence, model driven-engineering, data-driven engineering, Knowledge management systems, visualisation</td></tr>
<tr><td>Data analytics for business intelligence and value creation out of production data</td><td>Production data handling and fusion techniques, data-driven engineering</td></tr>
</table>

Table 9: Contribution of main I4.0 technologies to selected production concepts

Technologies / **Production Concepts**	IIoT, CPS	BDA	Simulation/ Emulation	Cloud/Edge/ Fog Computing	AI/ML/DL	AR/VR	Robots/Cobots	Additive Manufacturing	Cyber Security	**Technologies** / **Production Concepts related requirements**
Digital Twin for machine life-cycle Improvement	***	*	***	*	**		***	*	***	Understand machine specification, Use of modelling and simulation tools, Interconnection of systems (Machines/PLC/Sensors/software applications)
Digital Twin for Cyber-Physical Production System Design	***	*	***	*	**	***	***	*	***	Use and selection of appropriate design technique and product development models, perform virtual commissioning,
Dynamic Production Planning	***	***	***	**	***		***	***	**	Use of production planning methods and tools, software development of industrial applications
Decision Support System for continuous production plans evaluation	***	***	**	*	***				***	Familiar with requirements engineering, Expert Systems, artificial intelligence
Data analytics for business intelligence and value creation out of production data	***	***	***	**	***			***	**	Production data handling and fusion techniques

Legend: * (low), ** (intermediate/mitigate), *** (high)

4.3. Quality Engineering

Quality 4.0 refers to the digitalization of quality management. It is the impact of that digitalization on quality technology, processes and people. LNS has identified 11 axes of Quality 4.0, which companies can use to educate, plan, and act[174]. Using this framework and research, leaders identify how Quality 4.0 can transform existing capabilities and initiatives. The framework also provides a perspective on traditional quality. Quality 4.0 doesn't replace traditional quality methods, but rather builds and improves upon them. Manufacturers should use the framework to interpret their current state and identify what changes are needed to move to the future state.

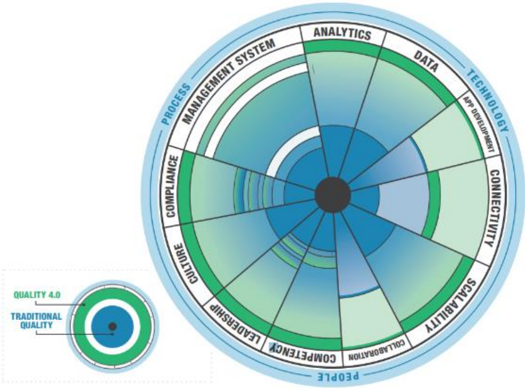

Figure 17: LNS Framework for Quality 4.0 [174]

4.3.1 Concepts, models and practices

Business and management models are essential to support Industry 4.0 adoption and foster sustainable value creation and competitiveness. Quality 4.0 (or Q4.0) combines quality management with digitalization and technology [175,176], which provides a management and process dimension to the digital transformation technology driver. Not only product and process quality are required for Industry 4.0 to improve flexibility and productivity, but also the quality management body of knowledge (encompassing models, systems, techniques, and tools) coupled with extensive application experience, which can support the planning, implementation, and improvement of Industry 4.0 processes. Q4.0 can, therefore, improve I4.0 quality and results. Empirical research addressing total quality management (TQM) and information technology (IT) show that while TQM had a significant impact on performance, and IT had a positive impact on TQM implementation, there were no significant performance improvements due to the direct application of IT. These findings suggest that I4.0 would largely benefit from Q4.0.

Nevertheless, research and innovations encompassing quality and digital transformation and technologies are scarce [176]. Consequently, quality and organizational excellence academicians and practitioners should engage in and make novel contributions to the Quality 4.0 theme if they want to ensure future relevance and minimize the risk that the technology dimension overtakes the arena. As highlighted by academicians [176], a clear quality focus and solid management systems are required for achieving comprehensive and enduring benefits from technological advancements. Quality and Industry 4.0 should be strategically and operationally integrated, with quality providing the methodology and tools to drive change and improvement.

In that regard, The European Foundation for Quality Management (EFQM) 2020 model is a comprehensive and updated business model that encompasses sustainability and shares features with Industry 4.0, emphasizing transformation and improved organizational performance, yet with different theoretical and practical foundations [176]. While not explicitly mentioning quality and excellence, the EFQM 2020 model has strongly embedded quality management principles and concepts, incorporating a system and improvement approach with a strong stakeholder (and customer) focus. The model provides a strategic dimension to Industry 4.0, complemented by criteria and guidance points that can support its application, monitoring, and improvement. However, due to the generic nature of the model, the criteria and guidance points need to be specifically tailored and detailed further for each business, for application of the quality methods, techniques, and tools. In other words, the EFQM 2020 model encompasses quality management models but should be complemented by more "hard" quality engineering approaches, methods, techniques, and tools.

4.3.2 Contributions of Quality 4.0 to the value chain

A recent study by the Boston Consulting Group (BCG), in partnership with the American Society for Quality (ASQ) and the German Association for Quality (Deutsche Gesellschaft für Qualität, DGQ), sought to better understand technology's role in addressing the imperative to transform quality management [177]. The study focused on the opportunities and challenges arising from Quality 4.0—the application of Industry 4.0's advanced digital technologies to enhance traditional best practices in quality management.

Participants in a survey conducted as part of the study acknowledge the importance of Quality 4.0 at all stages of the value chain. Nevertheless, they see manufacturing and R&D as the areas that will benefit most from improved quality. The perceived importance to manufacturing reflects the visibility of value created on the shop floor. Participants also recognize the benefits of applying Quality 4.0 in R&D to improve design and embed quality into new products, and they understand the opportunity to capture quality-related improvements in value chain steps that are traditionally viewed as being outside the scope of the quality function, such as logistics and sales.

Participants point to predictive analytics, sensors and tracking, and electronic feedback loops as the most important technologies for driving impact. More than 60% say that predictive analytics will significantly affect quality performance and the bottom line within five years, compared with only 16% who cite a significant impact today. The expected increase in importance suggests that investments in predictive analytics for quality management will be a major source of competitive advantage.

Other high-impact technologies include digital twins (digital replicas of physical objects and processes) and simulation testing. By allowing companies to gather and aggregate data continuously, these technologies enable preventive maintenance and optimized production, thereby reducing the likelihood that a company will inadvertently release poor-quality products.

In the subsections that follow, we discuss the contributions of Quality 4.0 in each area of the value chain (cf. Figure 18).

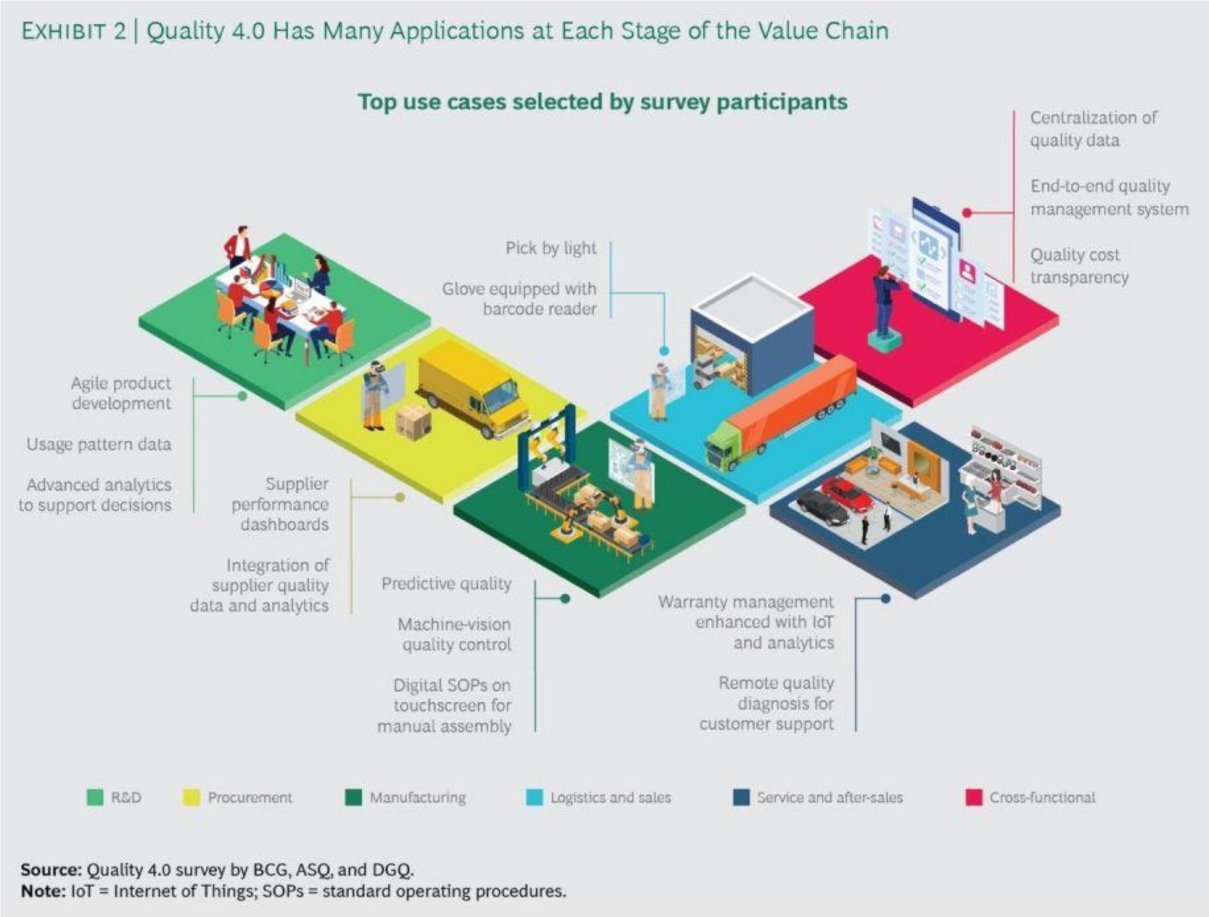

Figure 18. Contributions of Quality 4.0 to the value chain [177].

4.3.2.1 Research & Development

Companies can use Quality 4.0 technologies, such as simulation testing and artificial intelligence (AI), to improve a design's robustness. For example, AI supports failure mode and effects analysis. By enabling and improving preventive quality, this use case helps eliminate potential failure points in the design of a product or process. In addition, companies can work with usage pattern data that sensors connected to the Internet of Things (IoT) capture to improve the design of future products in ways that enhance quality by preventing failure. As reported in [177], survey participants consider agile product development to be the most important use case in R&D. By replacing the traditional waterfall approach to development with an agile way of working, a company can achieve significant time and cost reductions in the development process. Because the agile approach facilitates cross-functional collaboration, it promotes more robust designs and improved quality outcomes. Digital tools for virtual design are important enablers of agile. They promote quality by accelerating test and validation cycles and making field data more accessible. As reported in [177], a major industrial goods company focused 90% of its Quality 4.0 investments on agile product development. Its goal was not only to deliver R&D projects on time and within the planned budget but also to improve the quality of the product at launch. The initiative owed its success to three building blocks: a well-crafted change management plan to promote organizational buy-in; top-management support; and external assistance in building capabilities. The impressive array of benefits included delivering projects within 50% of the traditional lead time, avoiding the typical 30% cost overruns, and boosting morale [177].

4.3.2.2 Procurement

Digital dashboards that track supplier performance give visibility to data, such as KPIs and quantities ordered and received. As reported in [177], this use case was the only one that more than 50% of survey participants say they are already implementing. Companies can use data on supplier performance to assess where quality risks exist in the supply chain and to deploy supplier development resources as needed. They can also use the data in procurement negotiations and contracting to boost their bottom line.

4.3.2.3 Manufacturing

As reported in [177], survey participants consider predictive quality, machine vision quality control, and digital standard operating procedures (SOPs) to be the most important use cases in manufacturing. Predictive tools give manufacturers unprecedented power to analyse massive amounts of data and discover correlations between critical variables. These insights enable companies to address the root causes of problems pre-emptively—before quality issues occur. Indeed, one expert observed that intensified regulatory scrutiny has made implementing this use case an imperative. “It’s no longer okay just to fix things,” he explained. Compared with manual inspection processes, machine vision technologies are less expensive to use and more effectively verify quality or detect quality issues at early stages of the production process. For their part, digital SOPs ensure that workers have the most up-to-date instructions.

In addition to the top three use cases selected by participants, other significant manufacturing applications include automatic root cause analysis, machine-to-machine communication to enable self-adjustment of parameters, and real-time process simulations. These applications promote product and process quality while eliminating waste.

Real-time quality control information system (RTQCIS) solutions capture up-to-the-minute manufacturing data, establish an operating context of the data, and ensure that it is stored to be accessible whenever needed at a later time for a variety of uses. The data should provide enterprise-wide visibility of the whole manufacturing process and quality measures [178].

4.3.2.4 Logistics and sales

By applying big data analytics to planning, a company can improve its ability to forecast the production volume it requires and to enhance the quality of its service. The benefits arise from the greater accessibility of data and from the use of improved technologies to support data processing and make compelling presentations to decision makers. For example, a process known as “pick by light” (using shelf lights to guide picking for order fulfilment) and the use of gloves equipped with barcode readers simplify a company’s logistics and improve the quality of its performance by making the process more reliable and less subject to human error.

4.3.2.5 Service and after-sales

Equipment in the field can communicate data regarding its condition to its manufacturer in real time via the IoT. By analysing the data, the manufacturer can generate insights that serve as an early warning of potential breakdowns related to product quality that could trigger warranty costs. A manufacturer can also enhance customer support by remotely diagnosing quality issues. For example, an equipment manufacturer stores field data centrally and uses an AI system to identify potential failures before they occur, enabling its technicians to fix problems prior to a breakdown. Similarly, field technicians can use mobile digital solutions, such as field service software, to enhance preventive quality and upgrade the customer experience. Such tools help improve service quality by giving technicians access to equipment histories, information on recent failure points, and service manuals that streamline diagnosis times and quote processing.

4.3.2.6 Cross functional

As reported in [177], the most important use cases involving cross-functional collaboration are centralization of quality data, an end-to-end quality management system, and quality cost transparency. A company must combine data sets from the quality systems of multiple functions to generate insights and address critical pain points across functions. In many companies, achieving this objective will entail creating connections between quality systems that each function currently maintains separately.

4.3.3 Application of Industry 4.0 technologies: examples

The literature provides several contributions of industry 4.0 technologies supporting quality management.
The adoption of an IoT platform can help to segregate clinically defect-related data, for the more effective prevention of quality defects and material savings [89]. Therefore, the main application of the IoT in quality management is quality defect detection in factory-made products.
Tao and Qi (2019) also discuss the capacity of BDA applied to product quality and monitoring manufacturing processes. Indeed, BDA enables accurate data analysis from the production process, making it easier to detect subtle changes in the quality of products.
The joint implementation of artificial neural network (ANN) and digital wearable gloves for classifying appropriate and defective operations in connector assembly though feedback signals on vibration and force in the fingers [179] have been tested.
Discrete event simulation is proposed to identify and assess different methods of product failure inspection by means of testing different ML techniques without disturbing physical production [180]. AI-related technologies could thus specifically support the detection of defects in assembly processes [181]. At the same time, augmented reality tools, such as visual wearables, may be used to compare the 3D CAD product model and the physical artefact [103,182]. In addition, Nagy et al. (2018) demonstrate an industrial case of using AR instead of paper-based checklists for quality checks. An AR-enabled method of detecting and placing industrial robot faults is proposed [183], while Muñoz et al. (2019) investigate a mixed reality approach for car body surface quality inspections [184].
The quality of design will be achieved by first understanding the customer needs, and big data can be used to effectively do so[185]. The big data will also enable the understanding of customers' needs in a holistic or all-encompassing manner, as almost all customers' needs can be mapped and analysed. In Kano model terms, the threshold/basic attributes, performance attributes and excite/delight attributes can be accurately analysed using big data. Therefore, from a design perspective, these attributes will help the organizations to design a better trade-off in design variables, that is, cost and value of the product.
Too much attention is paid to quality control after product manufacturing and during exploitation (usage). The data pertaining to the usage of the product will be relayed back to the designers through end-to-end integration of Industry 4.0 [186]. Therefore, user needs can be better mapped and better products and services will be designed by the manufacturers. The quality of performance can be effectively monitored by collecting and analysing the product usage data in customer's hands in an automated manner using artificial intelligence. Moreover, the performance data will also be an important design input to continuously improve the product and services[175,187].
Following research projects deal with the concerns related to quality management.

I4Q: Industrial Data Services for Quality Control in Smart Manufacturing (H2020 funded research project, https://www.i4q-project.eu/). I4Q provides a complete solution consisting of sustainable IoT-based Reliable Industrial Data Services (RIDS) able to manage the huge amount of industrial data coming from cost-effective, smart, and small size interconnected factory devices for supporting manufacturing online monitoring and control. The i4Q Framework will guarantee data reliability with functions grouped into five basic capabilities around the data cycle: sensing, communication, computing infrastructure, storage, and analysis and optimization; based on a micro service-oriented architecture for the end users. With i4Q RIDS, factories will be able to handle large amounts of data,

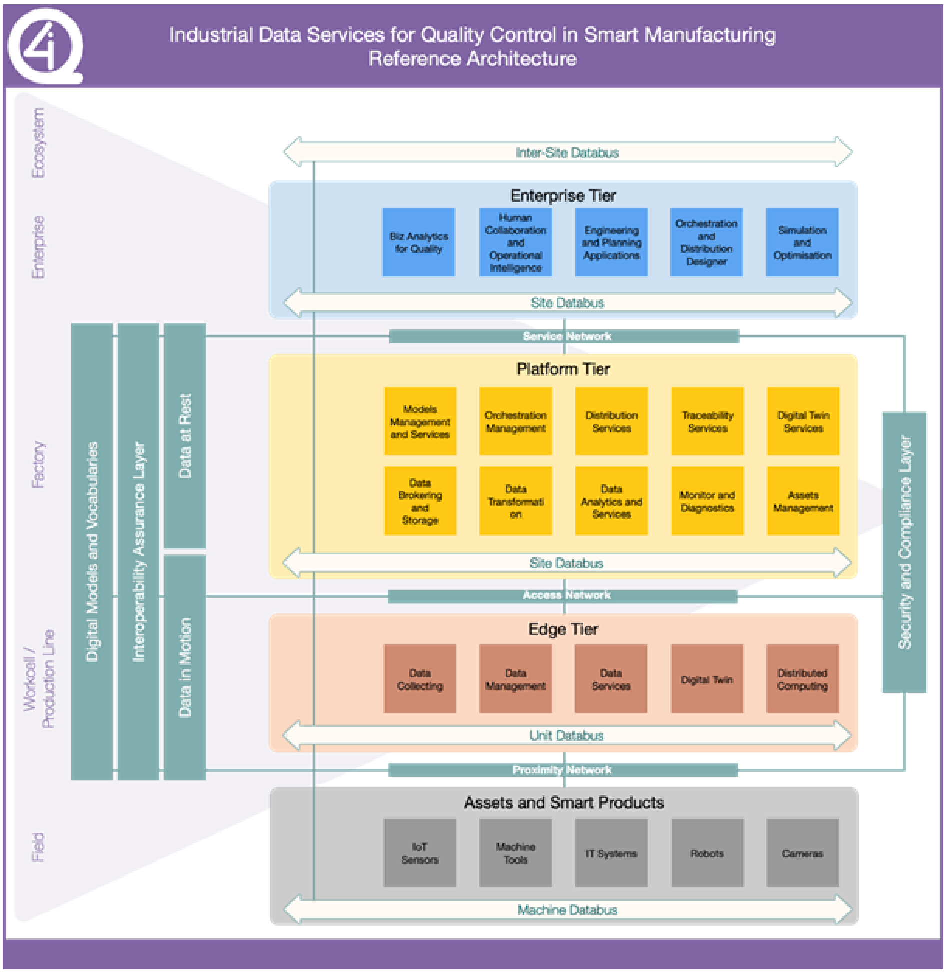

Figure 19: I4Q architecture

achieving adequate levels of data accuracy, precision and traceability, using it for analysis and prediction as well as to optimize the process quality and product quality in manufacturing, leading to an integrated approach to zero-defect manufacturing. i4Q Solutions will efficiently collect the raw industrial data using cost-effective instruments and state-of-the-art communication protocols, guaranteeing data accuracy and precision, reliable traceability and time stamped data integrity through distributed ledger technology. i4Q Project will provide simulation and optimization tools for manufacturing line continuous process qualification, quality diagnosis, reconfiguration and certification for ensuring high manufacturing efficiency and optimal manufacturing quality.

ViProQAS: Visual Product Quality Auditing System (German funded research project). In the context of Industry 4.0, the first software solutions are on the market that focus on operational planning and implementation of quality parameters and processes defined in computer aided quality (CAQ) systems. The recording and documentation of these solutions is mostly web- or app-based. They help to achieve end-to-end digitization for processes accompanying production. At present, however, product quality is primarily ensured by spot quality checks and product audits. Due to the complexity and variety of products and the large number of possible errors, these processes are primarily done manually. Technical assistance systems for these manual processes can contribute to an increase in process reliability and can reduce the duration of an audit.

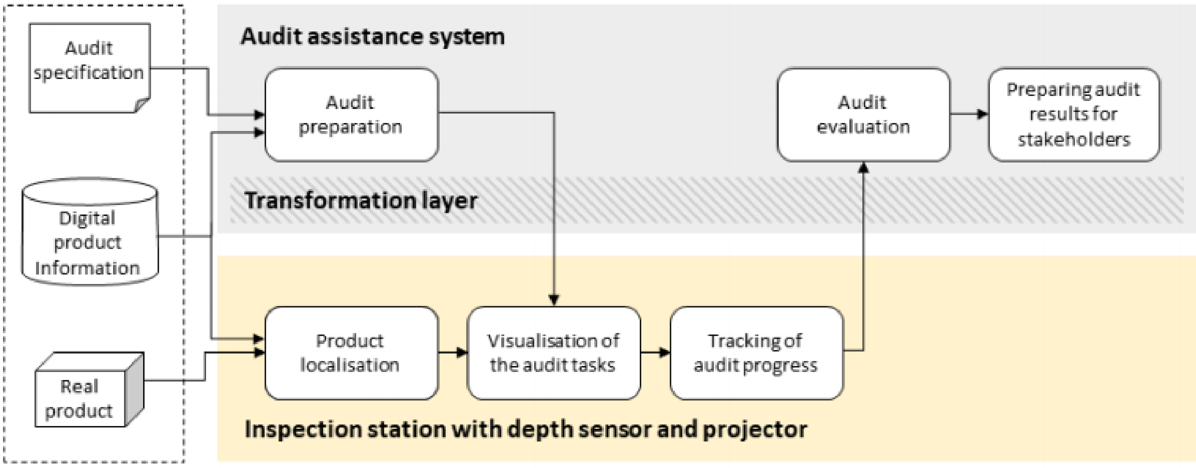

Figure 20. ViProQAS architecture

Current systems map the inspection process in a process-oriented manner, but do not provide direct support on the product. Approaches using AR glasses provide initial solutions for this, but the possibility of cooperative work through simultaneous visualization for all participants is not possible. The goal of ViProQAS is the direct visualization of the test steps on the component or product. The process progress should be recognized automatically during the inspection, which enables a complete documentation of the audit. A digital twin (DT) is created for the products to be audited, which contains the test instructions adapted for visualization. The DT serves as an administration shell to exchange information between the test bench and the CAQ. The visualization of the test procedure is made possible by means of projection on the test object. This projection is oriented to the position of the real object. Recording in detection by the use of depth cameras and gesture recognition is adopted. The innovation here is both the focus on the area of quality processes and the connection of visualization and recording as well as the control and documentation of the processes.

SealingQuality: Mobile inspection system for soft sealings with pseudometric shaped surfaces (German funded research project). There is a wide range of possible applications for sealants, with the greatest added value being achieved in the automotive and aircraft industries. The aim of the project is to develop a mobile documentation and inspection system for the application and evaluation of sealants with pseudometric freeform surfaces. The system is to be developed on the basis of the application and quality inspection of soft gaskets and is also to be used in various other applications. By using deep learning algorithms, a "universal" inspection system for soft seals will be developed, which can be continuously re-trained and offers high reliability. The system is to be designed as a mobile system, which is worn on the body in direct human-technology interaction and operated in real time.

Manufaktur 4.0: Quality-oriented production control and optimization in food production (German funded research project). The project develops a digitalised, quality-based production planning and control system for food production. The system focus on an optimal use of raw materials (e.g. reduction of the storage time of sensitive raw materials). The development should lead to a better operating grade of the production facilities and an optimization of their energy consumption as well as to an optimized bin management and especially to an increase of the product quality (taste). In order to achieve the objectives, raw material-specific quality-time profiles will be analysed and integrated in an IT-based procedure for quality-oriented production planning and control, which will be implemented as a prototype by the project partner.

Safe Processes: Inspection and logistic quality control of micro manufacturing processes (German funded research project). Safe Processes implements a method for an automated quality inspection of cold formed micro parts. This method has to be integrated on the existing demonstrator platform. The result will be a fast and calibrated 3D-metrology system that can automatically measure deviations of object geometries in a measurement volume of about 1 mm3. Thereby in addition to deviations from the object geometry, undesired surface imperfections can be detected, which may be within the tolerances but still weaken the structure of the thin-walled components. Thus, the fast acquisition of the micro parts surface turns from a random sample inspection, being developed throughout the 2nd phase, into a 100% inspection.

4.3.4 Required capabilities

Quality 4.0 is among the many developments that are giving rise to the “factory of the future,” in which digitally enhanced plant structures and processes increase productivity and flexibility in the factory and throughout the supply chain. Digital technologies can help improve quality in various ways. For example, companies can monitor processes and collect data in real time and apply analytics to predict quality issues and maintenance needs. Digital tools also enable people to do their jobs faster, better, and at reduced cost.

The Boston Consulting Group (BCG) survey and study [177] confirmed that technology is only one piece of a broader quality transformation that must also focus on people and skills. Although companies recognize that Quality 4.0 can create substantial value, few have defined a detailed strategy and launched an implementation program. Survey participants identify a shortage of skills as the main impediment. Notably, participants regard soft skills (such as change management, communication, and teaming) as the most critical skills for success, even as they acknowledge the need to improve their analytics and big data skills.

Taken together, the findings point to the need for companies to accelerate their adoption of Quality 4.0. Success requires a multifaceted approach that addresses the full range of strategic, cultural, and technological issues. Companies that master the challenges will be rewarded not only with lower defect and failure rates but also with competitive advantage in the form of greater customer satisfaction and improved operational efficiency.

Table 10: Concepts and corresponding requirements and needs for Quality 4.0

Quality Concepts (PC)	Quality Concept's Requirements (PCR)	Expected Capabilities	
Quality control steps design during product design Quality control steps optimisation during product industrialization In-process quality control during manufacturing Quality control steps post-manufacturing and before batch release Quality control steps during the first exploitation phase Long-term quality control during product exploitation	Establish and implement quality standards, Monitor workflows, processes, and products, Create quality documentation, Collaborate with operations managers to identify opportunities for improvements to workflow and controls, to ensure they comply with health and safety codes and regulations, Review systems and processes to develop continued improvements and efficiencies Inspect and test processes and products to ensure they meet or exceed standards Use of technologies for inspection, anomaly detection Understanding of product requirements	• Requirement Engineering and Modelling • Digitalization • Management systems (e.g. Six sigma) • Quality control methods (e.g. SPC) • Product Design • Guidelines and DIN standards • Real-time asset monitoring • Real-time tracking and traceability • Event-driven, collaborative, synchronized, smart, flexible, reconfigurable quality control scheduling • Data mining techniques • Performance analytics	• Collaborative, green energy-aware, automatic DIK management • ICT protocols and standards • Simulations for quality prediction • Decision-making Systems, Prognosis, Diagnosis, Cognition and intelligent Perception • Self-thinking, self-learning, self-decision-making, self-execution, and self-improvement • Visualisation, Virtualisation • Servitization (e.g. quality-as-a-service) • Project management

<table>
<tr><th>Quality Concepts (PC)</th><th>Quality Concept's Requirements (PCR)</th><th colspan="2">Expected Capabilities</th></tr>
<tr><td>Real-time (or near real time) Quality control in manufacturing</td><td>Use of enabling technologies for data gathering, processing and storage. Selection of appropriate quality control strategy and technique</td><td rowspan="3">- Digitalization
- Requirement Engineering and Modelling
- Management systems (e.g. Six sigma)
- Quality control methods (e.g. SPC)
- Product Design
- Guidelines and DIN standards
- Real-time asset monitoring
- Real-time tracking and traceability
- Event-driven, collaborative, synchronized, smart, flexible, reconfigurable quality control scheduling
- Data mining techniques
- Performance analytics</td><td rowspan="3">- Collaborative, green energy-aware, automatic DIK management
- ICT protocols and standards
- Simulations for quality prediction
- Decision-making Systems, Prognosis, Diagnosis, Cognition and intelligent Perception
- Self-thinking, self-learning, self-decision-making, self-execution, and self-improvement
- Visualisation, Virtualisation
- Servitization (e.g. quality-as-a-service)
- Project management</td></tr>
<tr><td>Tracking and traceability</td><td>Use of IIoT hardware and software tools and novel technologies for data generation, gathering and fusion

Use of techniques for Dashboarding and reporting for more traceability</td></tr>
<tr><td>Non-conformity decision making</td><td>Competencies in requirements engineering, Anomalies detection, use of enabling technologies for to support decision-making processes</td></tr>
</table>

Table 11: Contribution of main I4.0 technologies to selected quality concepts

Technologies / Quality Concepts	IIoT, CPS	BDA	Simulation/ Emulation	Cloud/Edge/ FoG Computing	AI/ML/DL	AR/VR	Robots/Cobots	Additive Manufacturing	Cyber Security	Technologies / Quality Concepts related requirements
Quality control steps design during product design	**	**	**	**	**	***	**	**	**	Quality policy
Quality control steps optimisation during product industrialization	**	**	**	**	**	***	**	**	**	Zero defect manufacturing by design
In-process quality control during manufacturing	***	***	***	***	***	***	***		**	On-line quality control Real-time (or near real time) Quality control
Quality control steps post-manufacturing and before batch release	***	***	***	***	***	***	***	*	***	Off-line quality control Defect detection Control tools
Quality control steps during the first exploitation phase	**	**	**	**	**	***	*	*	***	Defect detection Defect prediction
Long-term quality control during product exploitation	**	**	**	**	**	***	**		***	Defect prediction

Legend: * (low), ** (intermediate/mitigate),*** (high)

5. Synthesis of required MPQ4.0 competencies, skills and abilities

The state of the art highlights the nine pillars, enabling technologies, of Industry 4.0 and the SoA reference architectures. The resulting paradigm has improved all components of manufacturing capabilities and thus redefined the boundaries of maintenance, production and quality activities. To achieve this, companies should not only integrate emerging technologies but also adapt their know-how and organizational structures. An important challenge is the employee qualification with the necessary competencies for the requirements of Industry 4.0.
In addition, Maintenance, Production and Quality (MPQ) Engineering require common capabilities that show up regularly in each field taken separately.

Based on the analysis of the SoA related to industry 4.0 and Maintenance-Production-Quality processes, we generated a set of necessary capabilities to cope with the elements of industry 4.0:

- Capability to achieve integrated Systems and Architectures
- Capability to enable collaborative, cooperative, Self/Emerging systems
- Capability to enable advanced, smart connectivity and connectedness
- Capability to embrace core manufacturing process automation and sustainability
- Capability to achieve DIK Lifecycle Management
- Capability to achieve prescriptive and adaptive Decision Support

For this issue, we propose an abstraction framework based on interrelated competencies, skills and abilities, which are associated with the set of identified capabilities. Interrelation of competencies means that each competence provides support for, and complementarity to, other competencies. Each competence involves a set of skills that collectively achieve the competence. Each skill involves a set of (know-how) abilities that regularly appear through the description of industry 4.0 projects and technology implementations reviewed in section 4.

5.1.1 Competence 1: Capability to achieve integrated systems and architectures

Industry 4.0 introduces a set of technologies, practices and paradigms that do not work standalone, but rather work collectively in synergy to achieve higher benefits, in terms of added value, quality of service and performance. Achieving MPQ4.0 success requires a new mind-set, as well as new methodologies, tools and practices to design, develop, and operate such systems in a more integrated, interoperable and coordinated way. Competence 1 brings an answer to this requirement. It focuses on abstraction capabilities and model-based engineering to design, develop, and operate MPQ4.0 processes in such a way to guarantee their synergistic operation within integrated architectures.

5.1.2 Competence 2: Capability to enable collaborative, cooperative and self-emerging systems

Industry 4.0 work environments are characterized by smart production objects and resources able to communicate, and process data, information, and knowledge in an autonomous and distributed way. Those smart production objects and resources are no longer inert/passive, but rather become active and can participate in the different data and decision-making processes involved in the MPQ4.0 engineering fields. This activeness creates new ways to interact between humans, computers/machines, products, and services. Therefore, there is a need to address these new interaction opportunities and possibilities in a systemic and comprehensive way. Competence 2 brings an answer to this requirement. It focuses on the skills necessary to achieve innovative interactions, between humans, between humans and computers/machines, and among computers/machines.

5.1.3 Competence 3: Capability to enable advanced and smart connectivity and connectedness

Industry 4.0 work environments require production objects, resources (including augmented operators/collaborators, machines, robots, logistics, storage and material/products), and facilities to be interconnected, to access, share and exchange data, information, and knowledge in a distributed/decentralized way, and in real time to create value, to participate actively in decision processes, and to enable advanced data analytics, business intelligence and decision making. Connectivity and connectedness are therefore essential requirements and represent backbone technologies of industry 4.0. Competence 3 brings an answer to this requirement. It focuses on the skills necessary to deal with the implementation, deployment and operation of the networking and computing infrastructure required through the management lifecycle of data, information, and knowledge. This networking and computing infrastructure spans the acquisition, transmission of data, information, and knowledge, as well as interconnection and operation of networking and computing systems, in a way to achieve systems of networked computing systems.

5.1.4 Competence 4: Capability to embrace core manufacturing process automation and sustainability

Whereas competence 1 focuses on designing and modelling transformation strategies and plans, it is necessary to be able to link those strategies to core manufacturing capabilities and technologies, and to deploy those strategies in manufacturing environments. Also, it is necessary to be up to date with the latest smart factory technologies, including processing and automation technologies. Moreover, it is necessary to operate the smart factory of the future in a sustainable and energy efficient way. Therefore, competence 4 brings an answer to these requirements. It focuses on the skills required to map enterprise strategies, architectures and transformation projects to core manufacturing capabilities, in order to be able to select the suitable technologies for the envisioned strategies. It also focuses on providing learners and trainees with the skills required to deal with the latest advances in core manufacturing, material processing and automation technologies. Strategies, capabilities and technologies are dealt with within a sustainability and energy efficiency framework to ensure lean, green and sustainable growth and value creation.

5.1.5 Competence 5: Capability to achieve data, information and knowledge (DIK) lifecycle management

In industry 4.0 work environments, data, information, and knowledge (DIK) represent the flows materializing value creation and enrichment. DIK become big (i.e., multiple sources, sizes, features, time scales, etc.), and go through a lifecycle that has to be managed timely, securely and reliably. Competence 5 brings an answer to these requirements. It focuses on the skills necessary to model complex systems involving big DIK and to manage their related infrastructure. It also focuses on the necessary skills to implement, deploy, and operate big DIK platforms to enable collection, storage, and processing of big DIK. It covers the necessary skills to preserve the quality of big DIK and brings essential data science and analysis tools. It finally covers big DIK governance and security issues.

5.1.6 Competence 6: Capability to achieve prescriptive and adaptive decision support

In industry 4.0 work environments, decision support mechanisms rely on big DIK to innovate and create new added value. Decision support requires being able to capture current system states, events and dynamics (what is happening), to understand and contextualize them considering history and past states (what happened and why did it happen), and to predict future states, events and dynamics (what will happen) in order to make proactive, anticipatory and prescriptive decisions (what to do to make it happen) in such a way to maintain or enhance performance and quality of service. Competence 6 brings an answer to these requirements. It provides skills to analyse big DIK to achieve diagnosis and prognosis. It provides skills to achieve competitive awareness and intelligence, predictive and prescriptive market and manufacturing system analysis.

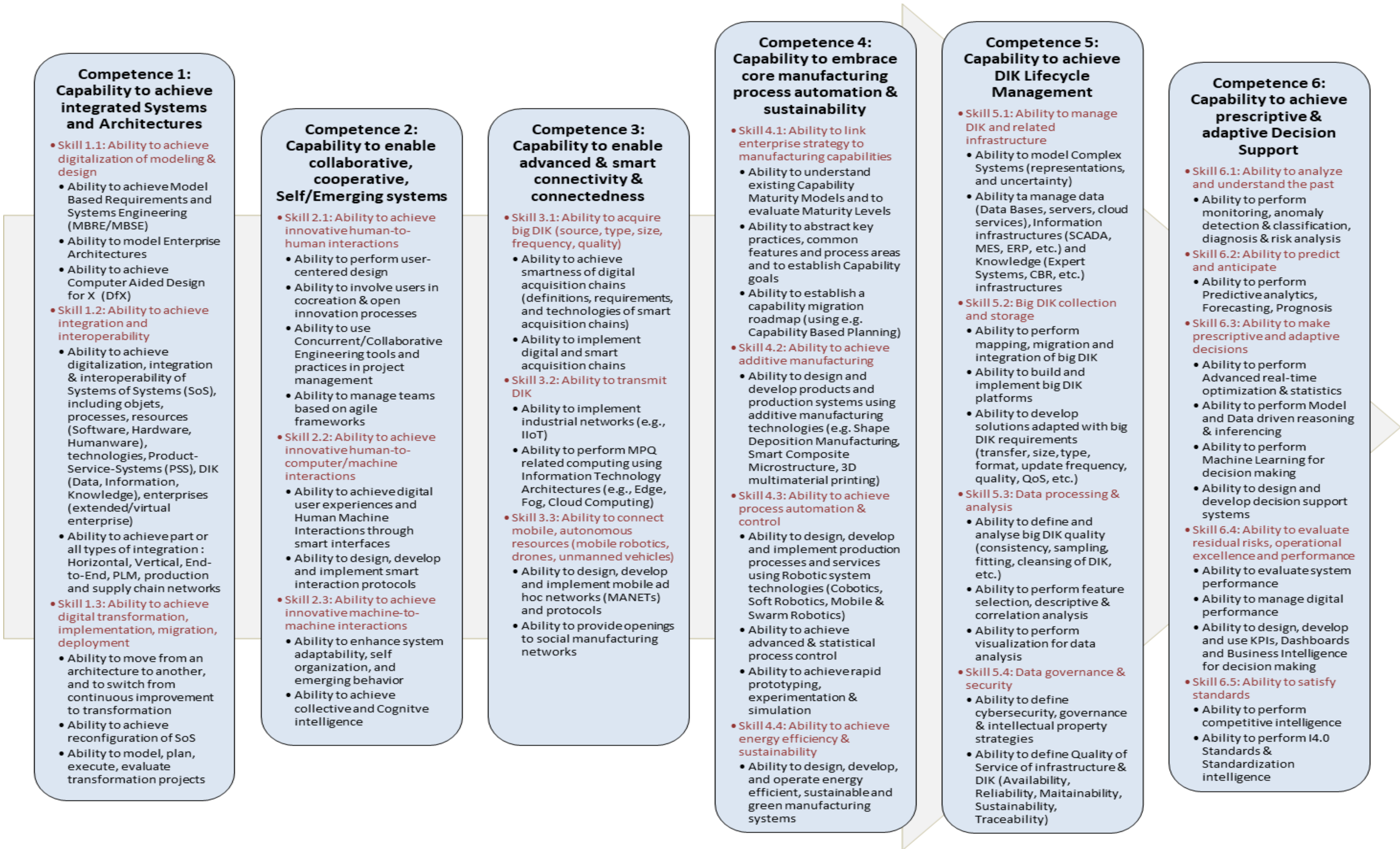

Figure 21. MPQ4.0 required competencies, skills and abilities.

6. Conclusion

The literature shows that the adoption of Industry 4.0 technologies results in people working in a digitized and networked workplace that promotes interaction with algorithms and robotics, as well as operating in a virtual world. These changes result in new job requirements for a unique and specialized skills set.

The availability of relevant skills and capabilities in local workforce (e.g., PC) will significantly influence the successful adoption of Industry 4.0 at the micro- and macro-level. In addition to that, the quality of skills and qualifications of the workforce will play a noticeable role in driving the innovation and competitiveness of companies. Conversely, a lack of the required skills set will result in a noticeable drop in performance and reduced competiveness in the companies.

Evidences show that developing countries in Africa are still faced with a critical shortage of professionals with the required MQP4.0 skills set. There is also a gap between the skills required and the skills developed in the MQP4.0 era. This could be because there is no clear awareness of the skills that meet MQP4.0 requirements. Thus, this makes it necessary to investigate closely the essential requirements for the skills in this digital economy, and to determine how these skills can be developed and incorporated into existing educational structures.

Given that the HEIs in PC need to develop and supplement theoretical knowledge with the required skills and competences that play a vital role. A number of studies emphasize that, to make a noticeable impact in this context, set of skills and competences must receive significant consideration including, among others, practical skills, technical skills, innovation skills, social and responsibility skills, collaborative skills, soft skills, hard skills, personal skills, behavioral skills, learning and information technology skills, domain skills, life and career skills coupled with entrepreneurship capability, business and industry knowledge, agility in problem solving, the ability to reshape processes, flexibility, and self-learning.

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