D2.3

State of the art survey

June 30 2021

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement No. 958264

DOCUMENT SUMMARY INFORMATION

Grant Agreement No	958264	**Acronym**	OPTIMAI
Full Title	Optimizing Manufacturing Processes through Artificial Intelligence and Virtualization		
Start Date	01/01/2021	**Duration**	36 months
Deliverable	D2.3: State of art survey (Due T0+6)		
Work Package	2		
Nature	Report	**Dissemination Level**	PU
Lead Beneficiary	UTH		
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DOCUMENT HISTORY

Version	Date	Changes	Contributor(s)
v0.01	Apr 1, 2021	Initial document. Contains: TOC, Methodology, AI for Industry, Metrology, Digital Twins, IoT, ZDM etc. TOC has been sent to partners; on objections expressed.	UTH
v0.02	Apr 5, 2021	Included: - Introduction/Background - EU-funded projects - Corrected text for EU-projects description	UTH
v0.03	Apr 11, 2021	Included partner input	UTH, UPV
v0.04	Apr 21, 2021	Included partner input	UTH, UNIMET
v0.05	Apr 28, 2021	Included graphs for: - AI for industry - AI for metrology	UTH, CERTH, FORTH
v0.06	May 05, 2021	- Included 'AI Ethics in Industry' - Included graphs for AI-enhanced digital twins	UTH, TRI, UNIMET, UAB
v0.07	May 06, 2021	Resolved missing refs (input from TRI, UAB) Changed structure as discussed: - Moved summarizing graphs to the "Summary section" as raw material, to be used later. - Updated headings. - Indicated where we should include more refs.	UTH, TRI, UAB
v0.08	May 08, 2021	Included "Ethics Conclusions"	TRI, UAB
v0.09	May 09, 2021	Additional information on Projects	UTH
v0.10	May 10, 2021	Included partner input	UTH, CERTH
v0.11	May 28, 2021	- Included input from FORTH - Updated Projects, included additional Refs to cover the whole period since 2015.	UTH, FORTH
v0.12	May 31, 2021	Minor additions	UTH
v0.13	June 1, 2021	Included summarizing graphs.	UTH

v0.14	June 4, 2021	Better description of the methodology protocol, additional references, updated graphs.	UTH
v0.18	June 11, 2021	Included FoF-Projects. Finalizing draft version for internal review.	UTH
RC01	**June 12, 2021**	**Release Candidate 01 – For internal review.**	**UTH**
Rev01	June 21, 2021	Addressed comments from internal review.	UTH, UAB
Rev02	June 26, 2021	Addressed comments fron internal review – round 2.	UTH, FINT
Final	**June 28, 2021**	**Final version to be submitted.**	**UTH**
Final check	June 30, 2021	Quality review check	ENG

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Logo	Partner	Country	Short name
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	FINT FUTURE INTELLINGENCE LIMITED	Cyprus	**FINT**
	IDRYMA TECHNOLOGIAS KAI EREVNAS	Greece	**FORTH**
	EVT EYE VISION TECHNOLOGY GMBH	Germany	**EVT**
	VISUAL COMPONENTS OY	Finland	**VIS**
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	PANEPISTIMIO THESSALIAS	Greece	**UTH**
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LIST OF ABBREVIATIONS

Abbreviation	Definition
A/IS	Autonomous and Intelligent Systems
AI	Artificial Intelligence
AI&R	Artificial Intelligence and Robotics
AI-HLEG	High Level Expert Group on Artificial Intelligence
AIoT	Artificial Intelligence of Things
ANN	Artificial Neural Network
API	Application Programming Interface
AR	Augmented Reality
AR/VR	Augmented Reality / Virtual Reality
B2B	Business to Business
CAD	Computer Aided Design
CNC	Computer Numerical Controlled
CNN	Convolutional Neural Network
CPMT	Cyber-Physical Machine Tools
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
CSR	Corporate Social Responsibility
CV	Computer Vision
DAQ	Data Acquisition System
DLT	Distributed Ledger Technologies
DNN	Deep Neural Network
DQM	Digitally enhanced Quality Management
DSS	Decision Support System

DT	Digital Twins
EFFRA	European Factories of the Future Research Association
ERP	Enterprise Resource Planning
FC	Fully Connected
FCN	Fully Convolutional Networks
FDM	Fused Deposition Modelling
FoF	Factories of the Future
GA	Genetic Algorithm
GBT	Gradient Boosted Trees
GDPR	General Data Protection Regulation
HCNN	Hierarchical Convolutional Neural Networks
HPC	High-performance Computing
HUD	Heads up Display
IC	Integrated Circuits
ICT	Information and Communication Technologies
IIMS	Integrated Information Management System
IIoT	Industrial Internet of Things
IoT	Internet of Things
IPR	Intellectual Property Rights
IRM	Information-rich metrology
IT2-FL	Interval Type 2 Fuzzy Logic
KSC	Kernel Spectral Clustering
LBP	Local Binary Pattern
LHC	Large Hadron Collider
LS-SVM	Least Squares Support Vector Machines

M2M	Machine to Machine
ML	Machine Learning
MLP-ANN	Multi-Layer Perceptron Artificial Neural Network
MLR	Multivariate Linear Regression
MOM	Machine Operations Management
MTCT	Machine Tool Cyber Twin
MVS	Machine Vision System
NAR	Nonlinear Auto-Regressive
NARX	Nonlinear Autoregressive Neural Network With Exogenous Input
NN	Neural Network
OEM	Original Equipment Manufacturer
OSPS	Open Scalable Production System
PCA	Principle Component Analysis
PCB	Printed Circuit Board
PHM	Prognostics and Health Management
PLI	Profit Loss Indicator
PMDT	Product Manufacturing Digital Twin
PPD	Product, Process, Data
PSO	Particle Swarm Optimization
PUF	Physical Unclonable Functions
R&I	Research And Innovation
ResNet	Residual Neural Network
RF	Random Forest
RGRN	Randomized General Regression Network
RIDS	Reliable Industrial Data Services

RNN	Recurrent Neural Network
RRI	Responsible Research And Innovation
RTS	Real-time Scheduling
SDKs	Software Development Kits
SIEM	Security Information and Event Management
SMEs	Small and Medium-sized Enterprises
SoA	State of the Art
SRD	Socially Responsible Design
SSMD	Single Shot MultiBox Detection
SVM	Support Vector Machine
vf-API	Virtual Factory Application Programming Interface
VFFS	Vertical Form Seal And Fill
vf-MW	Virtual Factory Middleware
vf-SK	Virtual Factory System Kernel
WEDM	Wire-Cut Electrical Discharge Machining
ZDM	Zero-Defect Manufacturing

Executive Summary

This report is in fulfilment of requirements for Deliverable D2.3 of OPTIMAI. The document reports the State-of-the-Art in related scientific fields and identifies relevant research initiatives. Information contained herein is the result of activities performed in Task 2.2 (State of the art analysis, existing and past research initiatives).

The key activities performed in this task are summarized in the following list:

- Short introduction to Industry 4.0 to support the relevance and necessity of artificial intelligence in modern industry.
- Assessment of the state-of-the-art within existing results coming from related projects, to identify which ones are relevant to OPTIMAI. This assessment was performed in terms of functionality provided, innovation capacity, technology, license, status, etc.
- Assessment of the state-of-the-art within relevant scientific domains, including Artificial Intelligence (AI) for Industry, Metrology, AI-enhanced Digital Twins, Internet of Things (IoT) sensors, Computer Vision and Augmented Reality.
- For the sake of completeness, a survey on ethical aspects is also performed. This is kept short since it is subject to other Deliverables of OPTIMAI.

The review methodology is described in detail, in terms of sources, search keys, criteria for selection/exclusion etc., so that this work is repeatable. 269 articles were finally considered for inclusion in this report.

Upon review of all relevant works, findings are summarized and discussed. The use of artificial intelligence technologies in various industrial fields is explored and investigated; enlightening graphs are produced to visualize the distribution and popularity of each AI-tech, implying its suitability for different purposes.

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1 Introduction

This report is in fulfilment of requirements for Deliverable D2.3 of OPTIMAI. The document reports the State-of-the-Art in related scientific fields and identifies relevant research initiatives. Information contained herein is the result of activities performed in Task 2.2 (State of the art analysis, existing and past research initiatives).

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- Assessment of the state-of-the-art within existing results coming from related projects, to identify which ones are relevant to OPTIMAI. This assessment was performed in terms of functionality provided, innovation capacity, technology, license, status, etc.

- Assessment of the state-of-the-art within relevant scientific domains, including Artificial Intelligence (AI) for Industry, Metrology, AI-enhanced Digital Twins, Internet of Things (IoT) sensors, Computer Vision and Augmented Reality.

1.1 Background

Information and communication technology has been developed rapidly in the last decades. Cloud computing, internet of things, big data analytics, artificial intelligence, etc. represent some examples that can change industry and induce intelligence. Smart industry should be able to face the growing challenges of the market, by achieving a better reduced production time, less waste, and increased quality in products and services.

To this cause, a huge number of smart sensors is required along the production line, including temperature sensors, flowmeters, pressure sensors, humidity sensors, vibration sensors, etc., which give real-time information about the status of production. The benefits of real-time monitoring are rather obvious; smart technologies enable real-time data collection from production sensors and implementation of faster and more accurate decision making. On the other hand, such an approach requires the computational capacity to collect, transfer and process vast amounts of data.

To alleviate such issues, Industry 4.0. employs AI technologies, mainly in the regime of machine learning. Although Industry 4.0 is expected to have a strong impact on all areas of manufacturing, two major sectors are of most relevance to OPTIMAI, namely Machine Tools and Maintenance.

1.1.1 Machine tools

There have been four major generations [1] of machine tools (Figure 1), timed even before the first industrial revolution:

- **Machine tools 1.0**. Mechanical tools driven by huge mechanical devices but manually operated. These are dated long before the start of the Industrial Revolution.

- **Machine tools 2.0**. The invention electronic devices in mid-20th century enabled numerical control and electronic drive of machinery.
- **Machine tools 3.0**. The computer era enabled industrial automation.
- **Machine tools 4.0**. The current generation of machine tools introduces the concept of Cyber-Physical Machine Tools (CPMT). These try to integrate advanced smart industrial tools towards improved flexibility, reliability, safety, and production efficiency.

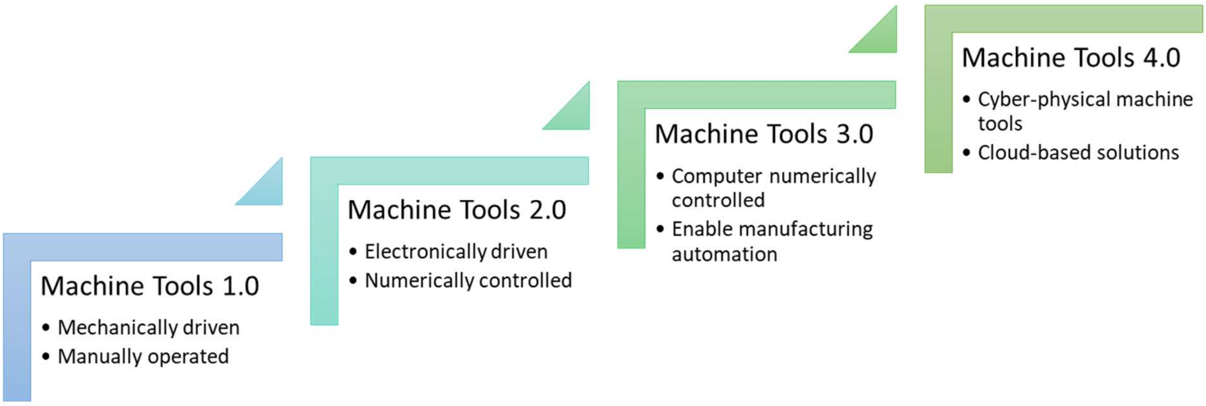


Figure 1. Evolution of mechanical tools.

CPMTs within Machine Tools 4.0 consist of three main parts:

- **Physical equipment.** Hardware and manufacturing apparatus; the actual heavy-duty machinery.
- **Smart devices.** Devices with embedded intelligence, usually in the form of machine learning and its variations.
- **Connectivity components**. Special devices that interconnect physical equipment to smart devices. These are not necessarily located in the same region; instead, they may communicate via a wide-spread network and use cloud/fog services.

CPMTs contain built-in computing devices that record and control industrial processes, with feedback loops supporting two-way real-time communication. Data is captured using various Data Acquisition Systems (DAQs), including sensors and cameras. Data control systems transmit data in real time. Special computational systems process this data and create a digital representation of the machine tool. This process raises the concept of Machine Tool Cyber Twin (MTCT). The MTCTs is not a simple virtual representation of the physical equipment, albeit it has built-in computing and decision-making components that monitor and control the physical devices and production processes. All data involved in the process may be submitted to central cloud systems for further analysis as historical data.

1.1.2 Maintenance

Maintenance plays a key role in reducing the risk and minimizing the effects of unexpected downtimes. Maintenance has evolved (Figure 2) from simple reaction to incidents (M 1.0) to a prescriptive (self-scheduled) process.

- **Maintenance 1.0**. In the era of Machine Tools 1.0, machines were simple and easy to repair. Machine operators were responsible for the maintenance of the equipment and their maintenance actions were limited focusing on errors that had already occurred.
- **Maintenance 2.0**. The second generation of maintenance introduced the idea to create a system of scheduled preventive repairs. The maintenance of machinery and equipment was carried out at predetermined intervals, while spare parts were available in advance.
- **Maintenance 3.0**. The third generation of maintenance integrates sensors to monitor the condition of the production lines. Unexpected incidents are timely identified and resolved.
- **Maintenance 4.0**. Not only does the fourth generation of maintenance target to diagnose incidents and trigger corrective actions, but also to predict errors in advance, using historical data along with experience from past events.

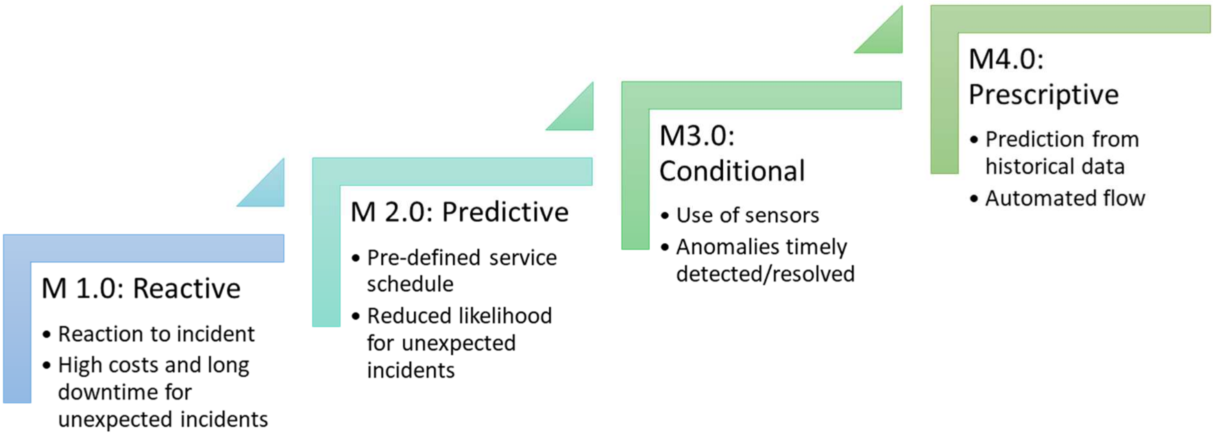


Figure 2. Evolution of maintenance.

M4.0 is also known as Smart Maintenance as it brings the concept of self-education by means of learning from collected data to predict imminent incidents. To enable M4.0, some critical technologies are required to elaborate, such as Internet of Things (IoT) and Industrial Internet of Things (IIoT), cloud computing, predictive analysis in its many flavors (fuzzy logic, neural networks, evolutionary algorithms etc.), targeting data collection, transmission, processing and — ultimately — decision making.

1.1.3 Relevance and scope of OPTIMAI

The study of every single aspect within Industry 4.0 goes far beyond the scope of OPTIMAI, which is to optimize manufacturing processes through artificial intelligence and virtualization. In practical terms, OPTIMAI is mostly concerned about Zero-Defect Manufacturing (ZDM); this means that integration of OPTIMAI in production lines envisions producing products of high quality with minimal rework and waste. Obviously, this is not straight-forward to achieve as it relies on numerous underlying components within production: machinery fault detection, resolution (prevention, detection, repair), management of product quality (metrology, classification), etc.

The production process is expected to benefit from OPTIMAI through its virtualization and simulation modules for production planning that will eliminate the need to allocate machine time for validation and preproduction runs that consume production resources and usually have low yield rates. Avoiding such test production runs will accelerate the completion of production orders and reduce its cost by minimizing scrap and optimizing production configuration. In addition, OPTIMAI will provide tools for the dynamic (re)-configuration and adjustment of production equipment, by directly exploiting quality control feedback to adjust machine parameters and realizing a context aware Augmented Reality (AR) environment, where human operators can rapidly reach informed production decisions regarding the calibration of machines in order to improve productivity and avoid deficiencies.

1.2 Objectives

The objective of this state-of-the-art analysis is to explore existing practices and success stories within the framework of Smart Factory and Factory of the Future (FoF), in order to establish the guidelines for further development within OPTIMAI. With this concept in mind, the following objectives have been determined:

- Make a survey on past research projects. Report key-findings, innovations, and limitations.
- Use peer-reviewed academic papers and articles to review best latest progress and State-of-the-Art practices within relevant scientific domains, including Artificial Intelligence for Industry, Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision, Augmented Reality and Zero-defect manufacturing.
- Implement a systematic literature critique to analyze and filter results of the conducted literature review.

Additionally, this survey goes beyond technicalities, and performs an:

- Assessment for AI Ethics in Industry.

2 Methodology

2.1 Systematic Literature Review

Global access to journal repositories, conference proceedings and technical reports, yields a practically endless pool of information. Thus, a systematic literature review was conducted to identify the best available resources and synthesize the current state of the art using evidence-based reports.

Following a systematic literature review method, reviews and meta-analyses can be accomplished with a degree of accuracy that can lead research in a well-structured manner. In a systematic review method, the least collection of elements is based upon evidence and meta-analyses that summarize and analyze scientific reliable literature by utilizing a structured method based on predetermined criteria/queries that can be used by various researchers. Different findings and ideas which are published in conventional papers by different researchers can be investigated with a correct and comprehensive analysis in a systematic review method.

2.2 Literature Planning Protocol

For the implementation of an efficient literature survey, a protocol was established based on ideas of Kitchenham [2]; this approach has been employed by other review surveys (e.g. Carvalho et al. [3]) with extraordinary results. The literature survey needs to consider the following tasks:

- Define scientific/research questions to be answered by the survey.
- Define a list of eligible sources for searching.
- Define inclusion and exclusion criteria.
- Assessment of eligible papers.

These tasks are explained in more details as follows.

- **Research questions**

  The literature survey should trigger responses to the following questions:

  - What AI/ML technologies are employed in existing smart factory applications/research within Industry 4.0?
  - What is the extent of involvement for each AI/ML technology in various smart factory fields?
  - What are the data used to apply AI/ML technologies in smart manufacturing?

- **Literature sources**

Only well-known database sources and respected publishers were considered; predatory journals/conferences and other sources of questionable quality were neglected. Thus, a literature review was carried out in the following databases:

- EFFRA [4]. The European Factories of the Future Research Association (EFFRA) is a non-profit, industry-driven association promoting the development of new and innovative production technologies. It is the official representative of the private side in the 'Factories of the Future' public-private partnership. More than 300 projects have been reported to date.
- Crossref [5]. Crossref is a not-for-profit membership organization that makes research outputs easy to find, cite, link, assess, and reuse.
- Google Scholar [6]. Google Scholar is a platform for broad searching of scholarly literature. It can search across many disciplines and sources: articles, theses, books, abstracts, and court opinions from academic publishers, professional societies, online repositories, universities and other web sites.
- Microsoft Academic [7]. Microsoft Academic is a platform to assist scientific research via Knowledge acquisition and reasoning, Semantic search and recommendation, Importance assessment and ranking, etc.
- Scopus [8]. Scopus is a well-known database for abstracts and citations. UTH has access to institutional subscription (via HEAL-Link [9]), thus its full search potential has been adequately exploited.

- **Inclusion criteria**

  To select the best papers, the following criteria were assessed, inspired by [10]:

  - Is the article related to industrial/manufacturing issues?
  - Does the title reflect the contents?
  - Does the abstract summarize the key components?
  - Is the literature review proper and up to date?
  - Is the aim of research clearly stated?
  - Is the methodology identified and justified?
  - Is the method of data collection valid and reliable?
  - Is the method of data analysis valid and reliable?
  - Are results presented in a clear way?
  - Are results generalizable and/or transferable?

- **Exclusion criteria**

The included articles were further processed by applying the following exclusion criteria:

- Works not related to AI/ML.
- Works dated before 2015.
- Websites and online material.
- Student theses.
- Brief reports.
- Papers describing frameworks, platforms, software, libraries etc.

Following the above selection protocol, a total of 165 research articles were initially found as suitable to be assessed within the literature review. These were listed by categories as previously defined and include Artificial Intelligence for Industry, Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision and Augmented Reality, Predictive Maintenance and Zero-defect Manufacturing.

It should be mentioned that the most popular on-line publishers such as IEEE Xplore, Elsevier, Springer, MDPI, IOP which offer open-access journal mining, along with scientific and technical search engine ScienceDirect helped considerably in this direction.

3 Literature Review

3.1 Distribution of articles by database

A thorough review was performed in the aforementioned databases; the search for relevant literature was accomplished by utilizing the keywords including "artificial intelligence", "machine learning", "deep neural networks", "metrology", "digital twins", "(industrial) internet of things", etc. Table 1 contains indicative phrases employed as primary keywords during the search process for relevant contents.

Table 1. Search strategy in different databases.

Database	Search Strategy
IEEE **Springer** **Elsevier** **Taylor and Francis** **MDPI** **ASME** **Others**	(Neural Networks, Deep Learning, Machine Learning, Support Vector Machine) AND (Metrology, Digital Twins, Industrial Internet of Things, Computer Vision, Augmented Reality, Quality Control, Predictive Maintenance, Zero-defect Manufacturing) "AI methods" in Abstract AND "Smart Factory" in Abstract. "AI methods" AND "Smart Factory" in Abstract. etc.

The search process described above returned 165 articles and all of them were reviewed. To be more explicit, the term 'article' was employed in a broader sense, including scientific papers, conferences proceedings, books, product demos and websites, platforms, AI frameworks, etc.

However, only 122 articles in form of scientific papers, book chapters, books and conference proceedings were considered for the purposes of the state-of-the-art analysis conducted for this deliverable.

The distribution by source (IEEE, Elsevier, Springer, etc.) of the considered 122 reviewed articles is shown in Table 2.

Table 2. Distribution of identified articles per publisher.

Publisher	Journal Papers	Conference Proceedings	Books and chapters	Total Articles
IEEE	10	20		**30**
Springer	13	4	3	**20**
Elsevier	32	3	1	**38**
Taylor and Francis	3			**3**
MDPI	5			**5**
ASME	2	2		**4**
Others	6	14	2	**22**

Total	71	43	6	**122**

3.2 Study selection and eligible papers

The outcome of 122 research articles was taken into consideration based on selection criteria. As per exclusion criteria, only qualified articles, book chapters and summary reports were chosen. Journal editorials, newsletters and papers which were not in English were excluded. Thesis reports, brief reports and websites were excluded too. According to inclusion criteria, we abided the following considerations: reference of the author, year of publication, whether it belongs to a journal or conference proceeding, the definition of the relevant smart manufacturing domains including Artificial Intelligence for Industry, Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision and Augmented Reality, Quality Control, Zero-Defect Manufacturing; its types and objectives, such as type of AI methods used, type of machine learning methods used, type of deep learning methods used, results and concluding remarks.

Furthermore, we proceeded by scrutinizing the abstract and summary of the chosen articles to investigate whether the selected articles fully satisfy the inclusion criteria. All insignificant and unrelated articles were discarded in this stage. Similarly, all academic research papers that did not match the inclusion criteria of AI methods were discarded too. In connection with this, 35 academic papers were excluded from the review process, whereas 130 articles were included as suitable according to the criteria discussed above.

Figure 3 indicates a chart related to classification. After reviewing all the remaining 130 papers, a second stage of articles extraction followed, in which papers describing IoT platforms, AI-based frameworks and open-source software libraries (keras, TinyML etc.) were excluded.

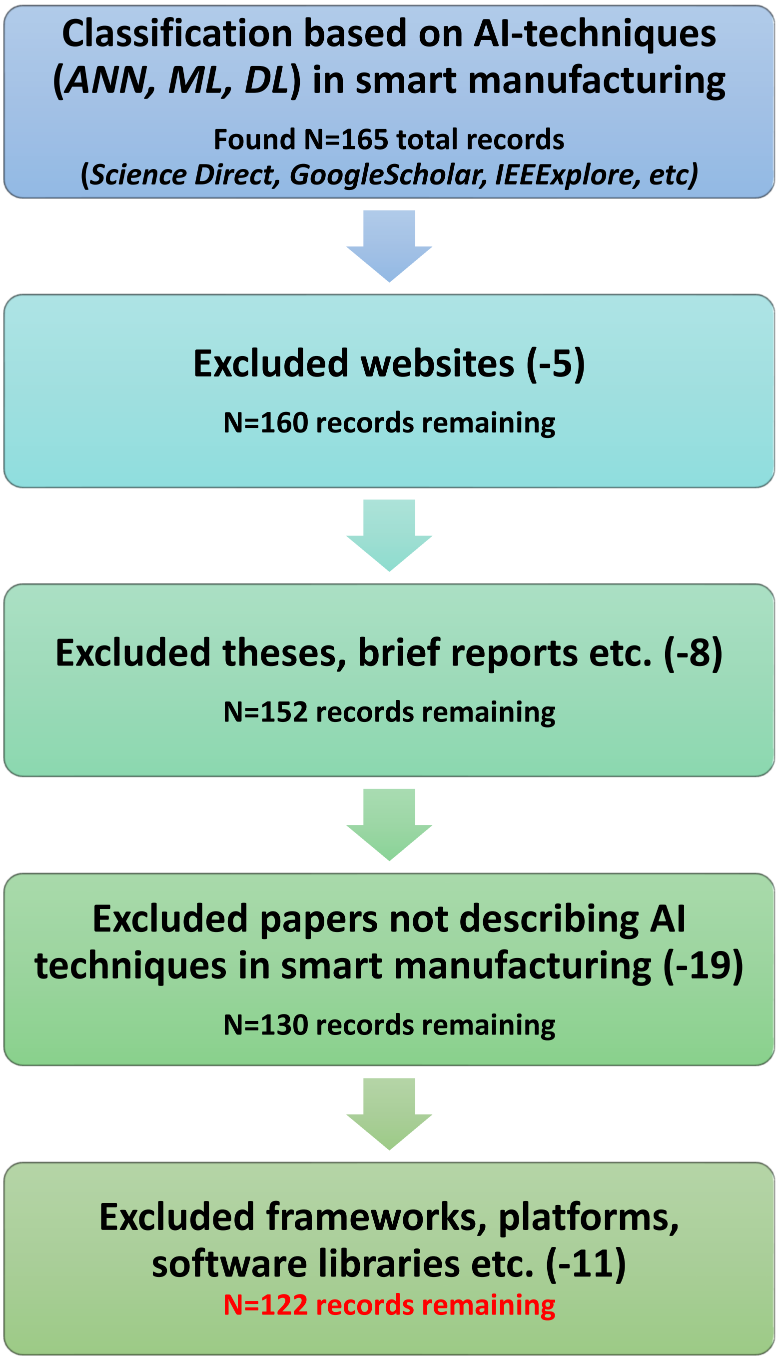


Figure 3. Flowchart for the implementation of the Literature Planning Protocol.

Finally, 122 academic research papers from 30 international scientific journals (among them are: J. of Manufacturing Systems, J. of Intelligent Manufacturing, Computers and Industrial Engineering, IEEE Trans in Industrial Informatics, Computers in Industry, Int. Journal of Production Research, IEEE Transactions on Instrumentation and Measurement, Simulation Modelling Practice and Theory) as well as 10 conferences proceedings (indicative Conferences: International Conference on Emerging Technologies and Factory Automation, International Workshop of Advanced Manufacturing and Automation, IOP Conference Series: Materials Science and Engineering, International Conference on Mechanical and Aerospace Engineering (ICMAE), IEEE Workshop on Applications of Computer Vision) which were published from January 2015 to April 2021, satisfied the eligibility criteria and were chosen for in-depth analysis and study. We thoroughly reviewed all selected articles and finally retained those which applied AI methods such as ANN, machine learning, deep learning, SVMs, Bayesian, linear regression etc. for smart manufacturing.

The following chart depicted in Figure 4, graphically represents the classification of articles by each relevant smart manufacturing domain, (AI for Industry, Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision and Augmented Reality, Quality Control, Zero-Defect Manufacturing), accompanied by the corresponding percentage.

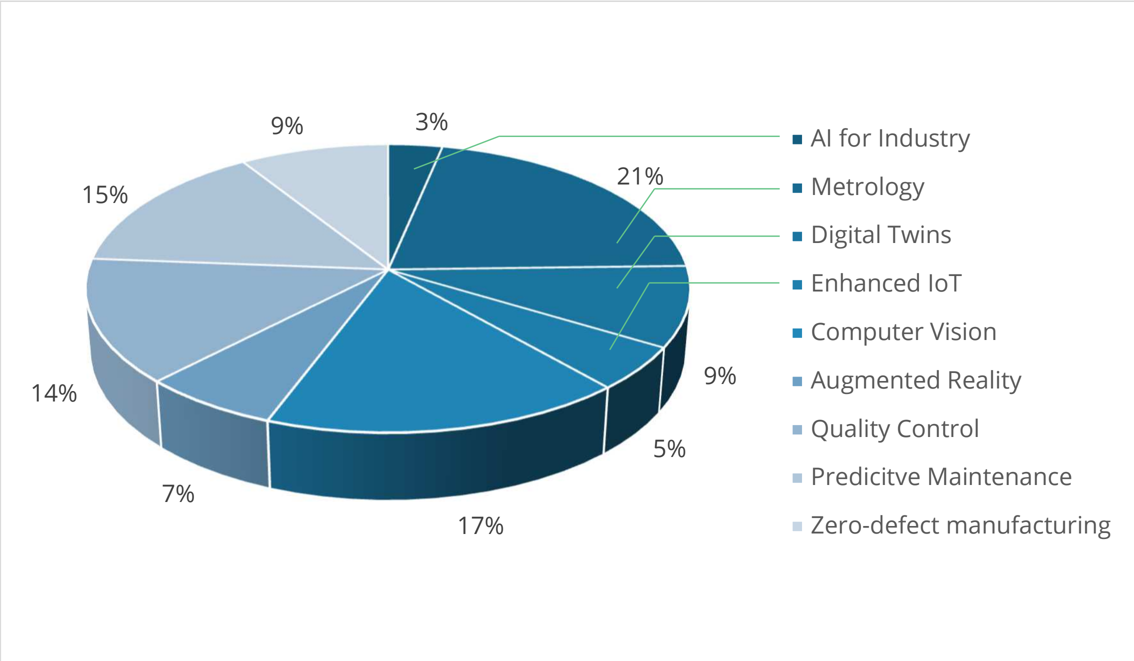


Figure 4. Classification of articles by each relevant smart manufacturing domain.

Regarding the ethics in AI for industry, a number of 46 articles was also reviewed focusing mainly on ethics guidelines and principles to form an ethical framework in the development and deployment of Artificial Intelligence technologies in smart manufacturing. The reviewed literature brings in certain ethical concerns, discussion and technological challenges that arise with AI systems, and deal mostly with the issues of privacy, safety, manipulation, transparency, fairness and accountability. Overall, AI technology adopted by Industry 4.0, can be implemented ethically and cautiously through the implementation of a set of rules leveraged to achieve the desired outcomes.

3.3 Distribution of projects in the EFFRA database

An assessment of state of the art and existing results deriving from related projects was accomplished, to properly identify which of these projects have competent relevance to OPTIMAI. For the purposes of this deliverable, 14 FoF-11 projects relevant to OPTIMAI (Calls: FoF-11-2016 Digital Automation - Novel architectures for factory automation based on CPS and IoT - Collaborative manufacturing and logistics, and FoF-11-2020: Quality control in smart manufacturing) as well as, other 14 EU-funded projects relevant to digitization in industry, quality control, ZDM, digital twins, computer vision and ZDM, have been extracted from the EFFRA database. The following Tables list the name of each project accompanied by its full title and the respective webpage (FoF-11 and EFFRA projects). After a careful examination of the related projects, it was decided that the projects in EFFRA are classified into three main categories according to the OPTIMAI objectives, namely Zero-defect manufacturing, AI-enhanced digital twins, and Computer vision and augmented reality. Furthermore, one more category for security information was considered. In what follows, each one of the selected EU-funded projects which are highly related to the main pillars of OPTIMAI, are presented.

Table 3. FoF-11 projects.

No.	Name	Title
1	https://www.i4q-project.eu/	**i4Q:** Industrial Data Services for Quality Control in Smart Manufacturing *DT-FOF-11-2020, 2021-2023*
2	https://dat4zero.eu/	**DAT4.ZERO:** Data Reliability and Digitally-enhanced Quality Management for Zero Defect Manufacturing in Smart Factories and Ecosystems *DT-FOF-11-2020, 2020-2024*
3	https://interq-project.eu/	**InterQ:** Interlinked Process, Product and Data Quality framework for Zero-Defects Manufacturing *DT-FOF-11-2020, 2020-2023*
4	http://www.autoware-eu.org/	**AUTOWARE:** Wireless Autonomous, Reliable and Resilient ProductIon Operation ARchitecture for Cognitive Manufacturing *FoF-11-2016, 2016-2019*
5	http://www.composition-project.eu/	**COMPOSITION:** Ecosystem for Collaborative Manufacturing Processes _ Intra- and Interfactory Integration and Automation *FoF-11-2016, 2016-2019*
6	https://www.connectedfactories.eu/	**ConnectedFactories:** Industrial scenarios for connected factories *FoF-11-2016, 2016-2019*
4	http://daedalus.iec61499.eu	**Daedalus:** Distributed control and simulAtion platform to support an Ecosystem of DigitAL aUtomation developerS *FoF-11-2016, 2016-2019*

5	http://www.digicor-project.eu	**DIGICOR:** Decentralised Agile Coordination Across Supply Chains *FoF-11-2016, 2016-2019*
6	http://www.disrupt-project.eu	**DISRUPT:** Decentralised architectures for optimized operations via virtualised processes and manufacturing ecosystem collaboration *FoF-11-2016, 2016-2019*
7	http://www.faredge.eu	**FAR-EDGE:** Factory Automation Edge Computing Operating System Reference Implementation *FoF-11-2016, 2016-2019*
8	https://www.nimble-project.org/	**NIMBLE:** Collaboration Network for Industry, Manufacturing, Business and Logistics in Europe *FoF-11-2016, 2016-2019*
9	http://www.safire-factories.org	**SAFIRE:** Cloud-based Situational Analysis for Factories providing Real-time Reconfiguration Services. *FoF-11-2016, 2016-2019*
10	http://vf-os.eu	**VFOS :** Virtual Factory Open Operating System *FoF-11-2016, 2016-2019*
11	http://www.scalable40.eu	**SCALABLE4.0:** Scalable automation for flexible production systems *FoF-11-2016, 2017-2020*

Table 4. EFFRA – Zero-defect manufacturing Projects.

No.	Name	Title
1	https://qu4lity-project.eu/	**QU4LITY** Autonomous Quality Platform for Cognitive Zero-defect Manufacturing 4.0 Processes through Digital Continuity in the Connected Factory of the Future *H2020-ICT-07-2018-2019, 2019-2022*
2	https://www.forzdmproject.eu/	**ForZDM:** Integrated Zero-Defect Manufacturing Solution for High Value Adding Multi-Stage Manufacturing systems *FoF.2016.03, 2016-2020*
3	https://www.stream-0d.com/	**STREAM-0D:** Simulation in Real Time for Manufacturing with Zero Defects *FoF.2016.03, 2016-2020*
4	https://www.z-fact0r.eu/	**Z-Fact0r:** Zero-defect manufacturing strategies towards on-line production management for European factories *FoF.2016.03, 2016-2020*
5	http://go0dman-project.eu/	**GO0DMAN:** Agent Oriented Zero Defect Multi-Stage Manufacturing *FoF.2016.03, 2016-2019*
6	http://www.ifacom.org	**IFaCOM:** Intelligent Fault Correction and self-Optimizing Manufacturing systems. *FoF.NMP.2011-5, 2011-2015*
7	https://www.zdmp.eu/	**ZDMP:** Zero Defect Manufacturing Platform *2019-2022, Call: DT-ICT-07-2018*
8	https://kyklos40project.eu/	**KYKLOS 4.0:** An Advanced Circular and Agile Manufacturing Ecosystem based on rapid reconfigurable manufacturing process and individualized consumer preferences. *DT-ICT-07-2019, 2020-2023*

Table 5. EFFRA – Artificial intelligence enhanced digital twins' projects.

No.	Project	Title
1	PRECOM Predictive Cognitive Maintenance Decision Support System https://www.precom-project.eu/	**PreCoM:** Predictive Cognitive Maintenance Decision Support System *FoF.2017.09, 2017-2020*
2	FORTISSIMO https://www.fortissimo-project.eu/about/fortissimo-2	**FORTISSIMO2:** Factories of the Future Resources, Technology, Infrastructure and Services for Simulation and Modelling *FoF.ICT.2015.09.a_Innovation, 2015-2018*
3	DataPorts Data Platform for the Connection of Cognitive Ports https://dataports-project.eu/	**DATAPORTS:** Data Platform for the Connection of Cognitive Ports *ICT-13-2018-2019, 2020-2022*

Table 6. EFFRA – Computer vision and augmented reality projects

No.	Project	Title
1	SERENA https://serena-project.eu/	**SERENA** Versatile plug-and-play platform enabling remote predictive maintenance
3	FACTORY2FIT https://factory2fit.eu/	**Factory2Fit** Empowering and Participatory Adaptation of Factory Automation to Fit for Workers
5	RECLAIM https://www.reclaim-project.eu/	**RECLAIM** Remanufacturing and Refurbishment Large Industrial Equipment

Table 7. Other related projects.

No.	Project	Title
1	PREVISION http://www.prevision-h2020.eu/	**PREVISION:** Prediction and Visual Intelligence for Security Information *H2020, 2019-2021*
2	KONFIDO https://konfido-project.eu/	**KONFIDO:** Secure and Trusted Paradigm for Interoperable eHealth Services *DS-03-2016, 2016-2019*

3.4 Results and Findings in European Projects

3.4.1 FoF-11 projects

3.4.1.1 i4Q

The main aim of **i4Q** [11,12] is to improve digital manufacturing through more reliable and effective data. I4Q will provide a complete solution to improve the quality of manufactured products aiming at Zero-Defect manufacturing. i4Q aims to provide an IoT-based Reliable Industrial Data Services (RIDS), a complete suite consisting of 22 i4Q Solutions. It will manage the huge amount of industrial data coming from cheap 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**. i4Q RIDS will include simulation and optimization tools for manufacturing line continuous process qualification, quality diagnosis, reconfiguration, and certification for ensuring high manufacturing efficiency, leading to an integrated approach to zero-defect manufacturing.

The main results of the project are to provide: the necessary strategies, methods, and key technologies to ensure data quality, turn data into information and actionable insights, strategies, and methods for process qualification as well as process reconfiguration and optimization using existing manufacturing data and smart algorithms.

3.4.1.1.1 Relevance to OPTIMAI

i4Q focuses on the reliability data obtained during the manufacturing procedure. OPTIMAI will concentrate on the optimization and AI technologies for quality control and ZDM, thus it will cooperate with i4Q RIDS by including simulation and optimization tools for manufacturing product line continuous process qualification, quality diagnosis, reconfiguration, and certification for ensuring high manufacturing efficiency, leading to an integrated approach to zero-defect manufacturing. CERTH and ENG are key partners in both i4Q and OPTIMAI, thus, they could act as liaison for experience and technology transfer. Furthermore, both in i4Q and

OPTIMAI, digital simulation tools of the manufacturing line procedures will be developed in order to detect, diagnose and validate the performance of the manufacturing operation.

3.4.1.2 DAT4.ZERO

DAT4.ZERO is a Digitally-enhanced Quality Management System (DQM) [13] that gathers and organizes data from a **Distributed Multi-sensor Network**, which, when combined with a DQM Toolkit and **Modeling and Simulation** Layer, and further integrated with existing **Cyber-Physical Systems** (CPS), offers adequate levels of data accuracy and precision for effective decision-support and problem-solving - utilizing smart, dynamic feedback and feed-forward mechanisms to contribute towards the achievement of **Zero Defect Manufacturing** (ZDM) in smart factories and their ecosystems.

The aim is to: Integrate smart, cost-effective sensors and actuators for process simulation, monitoring and control, develop real-time data validation and integrity strategies within actual production lines, demonstrate innovative data management strategies as an integrated approach to ZDM, develop strategies for rapid line qualification and reconfiguration.

The primary objectives are summarized as:

- Develop and demonstrate an innovative DQM system and deployment strategy for supporting European manufacturing industry in realizing ZDM in highly dynamic, high-value, high-mix, low-volume production contexts, by effective selection and integration of sensors and actuators for process monitoring and control.
- Design a DQM platform with an architecture that provides reliable and secure knowledge extraction to ensure integrity of data.
- Provide strategies for advanced real time data analysis and modeling in multiple domains and sectors that will increase quality, reduce ramp-up times and decrease time-to-market.

The EU-funded DAT4.ZERO project will develop a Digitally-enhanced **Quality Management** (DQM) system to prevent **faults**. With the use of smart, dynamic feedback and feed-forward mechanisms, the project will contribute towards **zero-defect manufacturing** in smart factories. The expected result is to eliminate manufacturing defects in highly dynamic, high-value, high-mix, low-volume production contexts. By doing this, DAT4.ZERO realize near-zero defect level of manufacturing (ZDM) for the European industry.

3.4.1.2.1 Relevance to OPTIMAI

OPTIMAI will cooperate with DAT4.ZERO to address the issue of handling large amounts of data, which can be used for health state assessment, fault detection and -possibly- fault prevention. Ultimately, OPTIMAI will benefit towards the optimization of the quality of manufacturing processes and products on its way towards zero-defect manufacturing. No OPTIMAI partners participate in DAT4.ZERO, yet open opportunities for future collaboration are possible.

3.4.1.3 InterQ

InterQ project [14,15] proposes a new generation of digital solutions based on intelligent systems, hybrid **digital twins** and **AI-driven optimization tools** to assure the quality in smart factories in a holistic manner, including process, product and data (PPD quality). The broad vision of InterQ project will allow controlling the quality of a smart manufacturing environment in an end-to-end approach by means of a PPD quality hallmark stored in a distributed ledger. The concepts of InterQ will be applied in three high-added value industrial applications.

The main objective of InterQ project is to measure, predict and control the quality of the manufactured products, manufacturing processes and gathered data to assure Zero-Defect-Manufacturing by means of AI-driven tools powered with meaningful and reliable data. Five modules will be developed:

- The InterQ-TrustedFramework module will implement a trusted framework using distributed ledger to exchange quality information.
- The InterQ-Process module of the project will obtain more meaningful process data for quality optimization. This data will be obtained using new sensors close to the tool and by AI-driven virtual sensors.
- The InterQ-Product module will predict the final quality of the processes using digital twins fed by experimental data and new digital sensors to measure the product quality.
- InterQ-Data module will check the reliability of data in two layers: in real time and based on historical and statistical analysis of the data streams.
- InterQ-ZeroDefect module will use the reliable information about the process and product quality to improve the production for Zero-Defect-Manufacturing by means of AI-driven applications.

Those 5 InterQ modules will contribute to the creation, extension and usage of the PPD (Product, Process, Data) Hallmark to fulfil the specific project objectives.

3.4.1.3.1 Relevance to OPTIMAI

Both OPTIMAI and InterQ pave the way towards increased product quality and zero-defect manufacturing; and both rely on AI technologies. Since they move in parallel roads, fruitful collaborations could be established to exchange fresh ideas on topics of common interest, such as AI-enhanced digital twins, AI systems and distributed ledger technologies, quality control etc. Both projects target the development of a respective TrustedFramework; thus, joining forces would be a beneficial European achievement.

3.4.1.4 AUTOWARE

AUTOWARE stands for "**Wireless Autonomous, Reliable and Resilient Production Operation Architecture for Cognitive Manufacturing**".

The main goal of AUTOWARE is to help those companies to implement Industry 4.0 by creating an open ecosystem that allows SMEs to access new digital technologies and exploit them in their factories. The main idea behind this project is the development of digital automation cognitive solutions for manufacturing processes through the implementation of open CPS ecosystem.

Its main high-level objective is to build an open consolidated ecosystem and single community that will lower the barriers of SMEs for cognitive automation application development and application of autonomous manufacturing processes.

Among the innovations delivered are the establishment of an open eco-system which facilitates the access to digitalization technologies to SMEs, the development of a business framework that migrates services towards digital automation, as well as unifying several European initiatives on cognitive autonomous products, production processes and equipment.

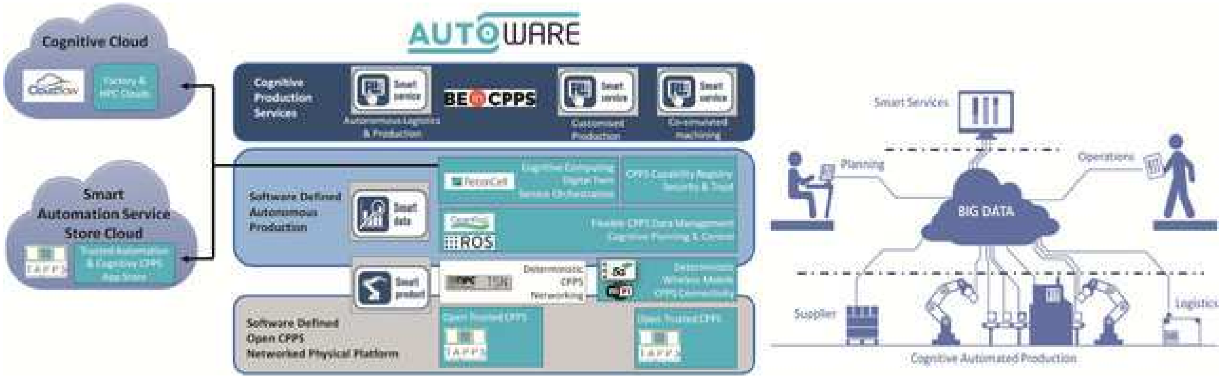


Figure 5. AUTOWARE reference architecture for cognitive manufacturing

AUTOWARE Industry 4.0 solutions are both hardware and software technologies within **Robotics and Automation**, **Cyber-Physical Systems**, **Fog Computing** and **Internet of Things**. AUTOWARE deals with service support through the development of cognitive and automation apps and collaborative robotics environments, cloud and HPC simulation and computation services, and open CPs trusted platforms incorporation, in an attempt to adopt Industry 4.0 technologies in Small and Medium-sized Enterprises. The integration of such digital technologies into manufacturing processes can help SMEs to stay more efficient in an increasingly competitive environment. All the technologies, developed within the project, make robots and machines work smarter together with people.

3.4.1.4.1 Relevance to OPTIMAI

AUTOWARE presents a communication management architecture to satisfy the wide range of communication requirements demanded by different industrial applications. In particular, the project provides a modular augmented reality platform for smart operator in production environment by using smarts glasses and an edge server. OPTIMAI could take advantage of this previous work to create AR interfaces for visualization of quality control results and suggestions. No OPTIMAI partners were involved in AUTOWARE, therefore, opportunities for future collaborations are open.

3.4.1.5 COMPOSITION

The **COMPOSITION** project represents an **Ecosystem for collaborative manufacturing processes**, whose main objective was to develop an integrated information management system (IIMS) to optimize the internal production processes by exploiting existing data, knowledge, and tools to increase productivity and dynamically adapt to changing market requirements (Figure 6). The project also developed an ecosystem supporting the interchange of data and services between factories and their suppliers, thus facilitating the entry of new market actors into the supply chain.

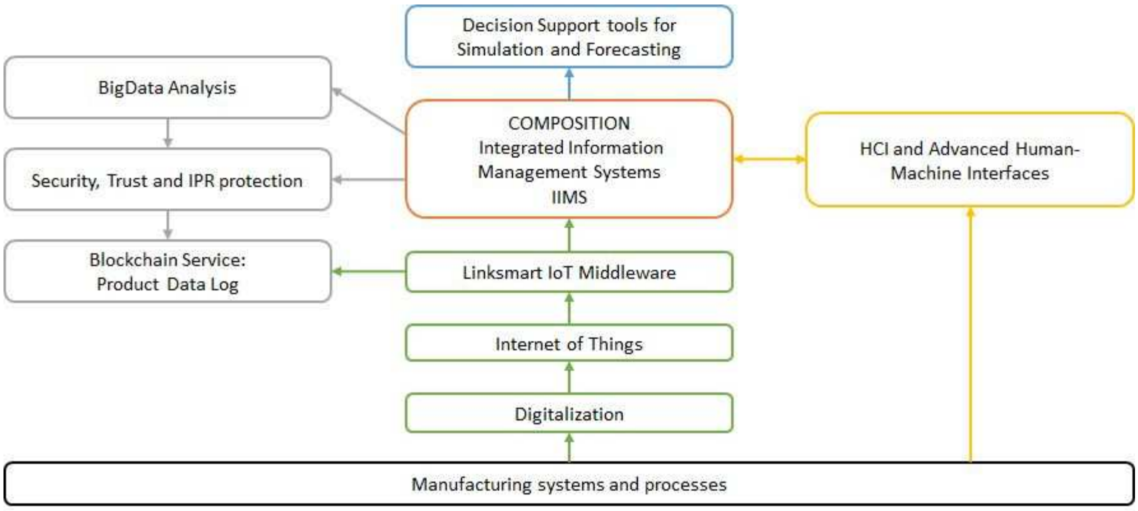


Figure 6. Composition Integrated Information Management System (COMPOSITION IIMS).

The project targeted to connect data within a factory's value chain as well as data and services between enterprises, overcoming the challenge of integrating the heterogeneity and complexity of data and handling confidentiality issues and the lack of standards.

Regarding the technology employed, a reference architecture was developed around digital models of business and production processes and enclosed a set of core multi-disciplinary and multi-domain integrated features such as **big data** analytics, **simulation/forecasting**, **data fusion**, interoperability, advanced human-machine-interaction, **Cyber Physical Systems** and **Internet of Things**. More specifically, the management system will consist of:

- Open connectors for data integration and real-time brokering.
- Big data analytics for pattern detection implementing a deep learning toolkit.
- Modelling of simulation tools for decision support.

3.4.1.5.1 Relevance to OPTIMAI

OPTIMAI will take advantage of the experience gained by COMPOSITION over the technologies deployed regarding big data analytics implementing ML and deep learning algorithms. OPTIMAI will also exploit the work regarding big data analytics for pattern detection to establish a methodology for detecting defects and predicting potential ones when equipment or materials are close to pre-determined margins of error, with the help of AI technologies. Moreover, data security, trust and IPR protection will offer great support to OPTIMAI on its way to develop data-driven techniques for secure sensor data mining and fault detection. To ensure a secure data management and exchange in manufacturing, COMPOSITIONS designed a security framework which include a blockchain component. This previous work will be considered when creating the OPTIMAI's blockchain-enabled ecosystem.

Both in Composition and OPTIMAI projects, simulations tools will be developed to train and enhance the efficiency of on-site workers. More specifically, CERTH/ITI developed in COMPOSITION various models and simulations comprising manufacturing operations, digital factory models and forecasting tools in production operations. These tools could also be investigated in the frame of the OPTIMAI project.

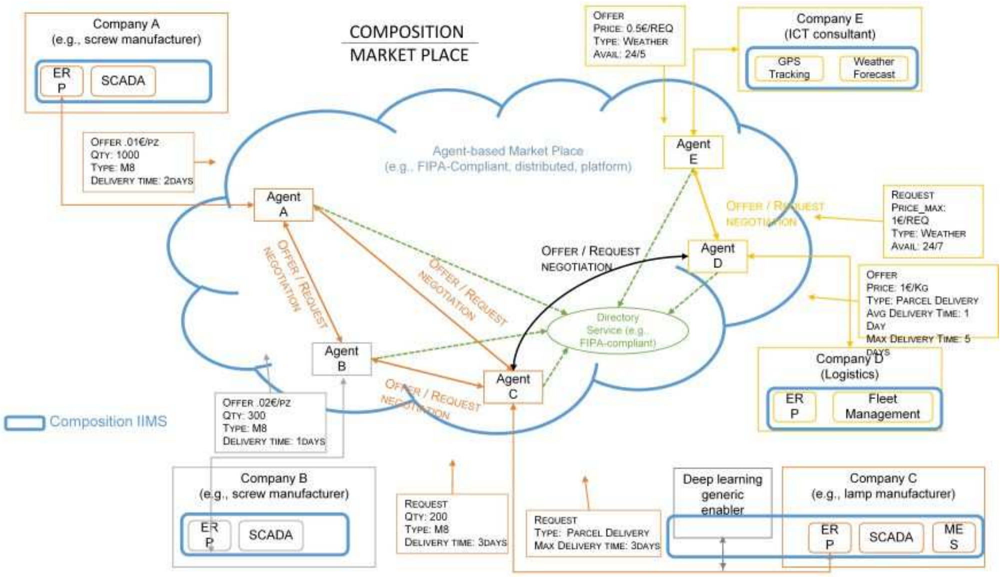


Figure 7. COMPOSITION technological framework.

3.4.1.6 ConnectedFactories

The **ConnectedFactories** project aimed at establishing a structured overview of available and upcoming technological approaches and best practices with regard to the digitalization of manufacturing. The project explored pathways to the digital integration and interoperability of manufacturing systems and processes.

Based on three pathways to the digitalization of manufacturing, such as: Autonomous Smart Factories, Hyperconnected Factories, and Collaborative Product-Service Factories, the **ConnectedFactories** project focuses on:

- Creating a common understanding of key enablers and cross-cutting factors for the development and deployment of digital technologies and digital platforms for manufacturing
- Deepening pathways by taking into account legacy systems, industrial requirements and challenges
- Situating inspiring research and industrial state-of-the-art cases, key enablers and cross-cutting factors along these pathways
- Matching of skills transfer offering with skills demand across Europe
- Engaging with the research and industrial actors in both European and local fora or ecosystems, bringing together manufacturing companies, technology and component suppliers, etc.

- Creating a broad awareness about the pathways, key enablers and cross-cutting factors, and about inspiring cases for SMEs
- Stimulating visibility and impact of Digital Platform projects (see also https://www.connectedfactories.eu/origin-project-outreach-and-impact)

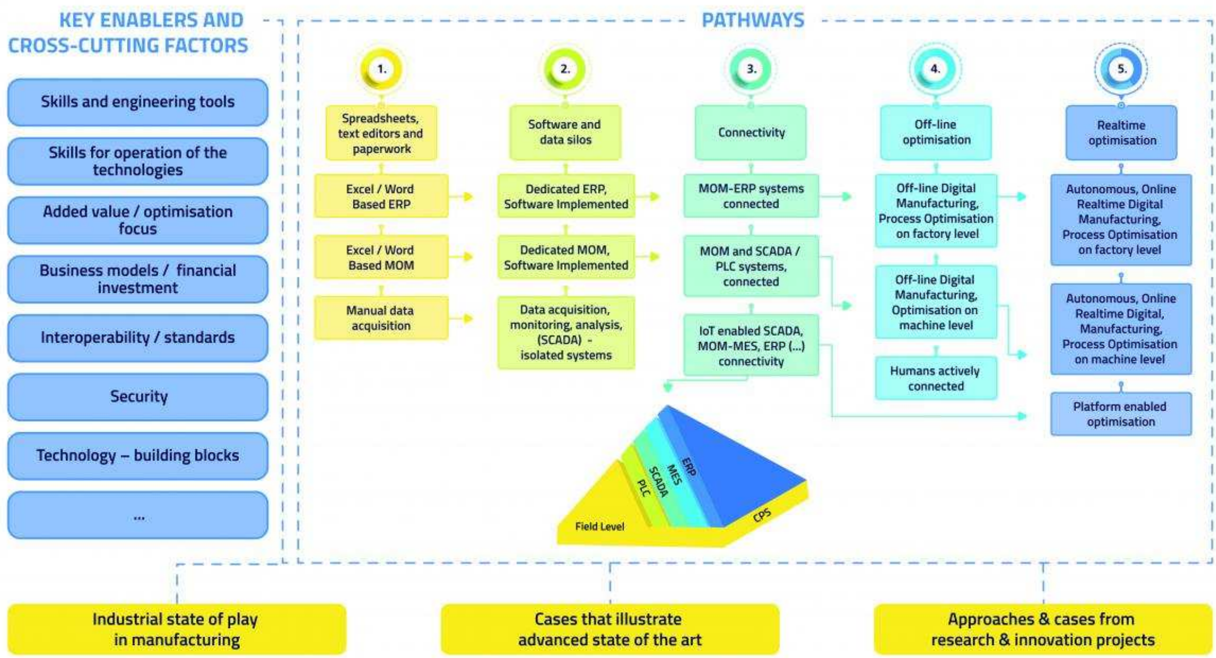


Figure 8. The ConnectedFactories framework.

The technologies utilized for the implementation of this project included **Software and data silos**, **dedicated ERP and MOM**, **IoT**, as well as the **FAR-EDGE platform**.

3.4.1.6.1 Relevance to OPTIMAI

ConnectedFactories mostly targets digitalization of manufacturing and focuses on technologies related to data and data communication using IoT etc. OPTIMAI could benefit from these technologies to develop its own AI-enhanced IoT and data-related approaches, like block-chaining, big-data analytics etc. In particular, OPTIMAI will benefit from decentralized automation architectures from manufacturers, including Edge/Fog computing, as well as Distributed Analytics and Simulation, to further explore and develop AI-based models aiming at achieving early defect-detection of the manufacturing components. ConnectedFactories exploits the FAR-EDGE platform, whose member was ENG – also member of OPTIMAI.

OPTIMAI's pilots could benefit from the collected ConnectedFactories information with regard to the digitalization of manufacturing. For example, the 'Digital Transformation Cases Catalogue' is a dynamic resource that brings together inspiring Industry 4.0 use cases and demonstrators. This catalogue focuses on providing a full insight of the digital transformation of processes that happen within the factory. This information is key to identify possible ways to accelerate and automate the processes that occur daily in factories. Additionally, ConnectedFactories warmly invited other national or regional projects to send them references of the use cases that the projects would like to appear and promote in the ConnectedFactories's catalogue. Joining forces with this project can be a win-win opportunity.

3.4.1.7 Daedalus

Daedalus project stands for "**Distributed control and simulAtion platform to support an Ecosystem of DigitAL aUtomation developerS**". It is conceived to enable the full exploitation of the CPS (Cyber Physical System) concept of virtualized intelligence, through the adoption of a completely distributed automation platform based on IEC 61499 standard, fostering the creation of a Digital Ecosystem that could go beyond the current limits of manufacturing control systems and propose an ever-growing market of innovative solutions for the design, engineering, production and maintenance of plants' automation.

Being a FoF project, Daedalus targeted the following key objectives:

- Ease the conception, development and distribution of intelligence into CPS for real-time execution of orchestrated manufacturing tasks.
- Foster interoperability of CPS from different vendors at orchestration-level
- Simplify the design, implementation and integration of optimal coordinating control intelligence of CPS.
- Enable near-real-time co-simulation of manufacturing systems as a fully integrated "service" of a CPS.
- Create a Digital Marketplace to simplify the matchmaking between offer and demand within the Ecosystem.
- Conceive a multi-sided business model for the Automation Ecosystem and the corresponding business plans for its Complementors.
- Foster the widespread acceptance of the Ecosystem platform to guarantee success and impact of Daedalus multi-sided market.

Daedalus proposes the deployment of an Automation Ecosystem for a multi-sided market based on a new generation of distributed intelligent devices (CPS) that, existing both in the real and in the cyber (simulated) world, can be aggregated, orchestrated and re-configured to exhibit complex manufacturing behaviours that optimize the performance of future shop floor.

This project deployed various technologies including **Cognitive and artificial intelligence (AI) technologies** and **machine learning**, **Intelligent machinery components**, actuators and end-effectors, ICT solutions for modelling and **simulation tools**, **Programming Languages** and other **Programming Frameworks – Software Development Kits (SDKs)**.

3.4.1.7.1 Relevance to OPTIMAI

Daedalus focused on the development of cyber-physical systems which is closely related to Digital Twin systems considered in OPTIMAI. Furthermore, it employed various AI technologies like cognitive intelligence, machine learning, intelligent machinery components etc., yet at less degree than OPTIMAI, which is fully focused on AI. Overall, OPTIMAI anticipates exploiting and integrate artificial intelligence (AI) technologies and machine learning algorithms in various manufacturing processes including the fields of computer vision, quality control and defect detection.

3.4.1.8 DIGICOR

DIGICOR – "**Decentralised Agile Coordination Across Supply Chains**" developed novel collaboration concepts and implemented an integrated platform that significantly reduces the burden to setup production networks and collaboration between SMEs. The main objective of this project was to address the integration of non-traditional, small but innovative companies or service providers into the complex supply chain of large OEMs. By providing relevant technology support at one place, the DIGICOR Collaboration Platform aimed to shorten the time to jointly respond to business opportunities and simplify the management and control of the production and logistics networks. It was open to third parties to add services for advanced analytics, simulation, or optimization etc. The platform provided seamless connectivity to the automation solutions, smart objects, and real-time data sources across the network.

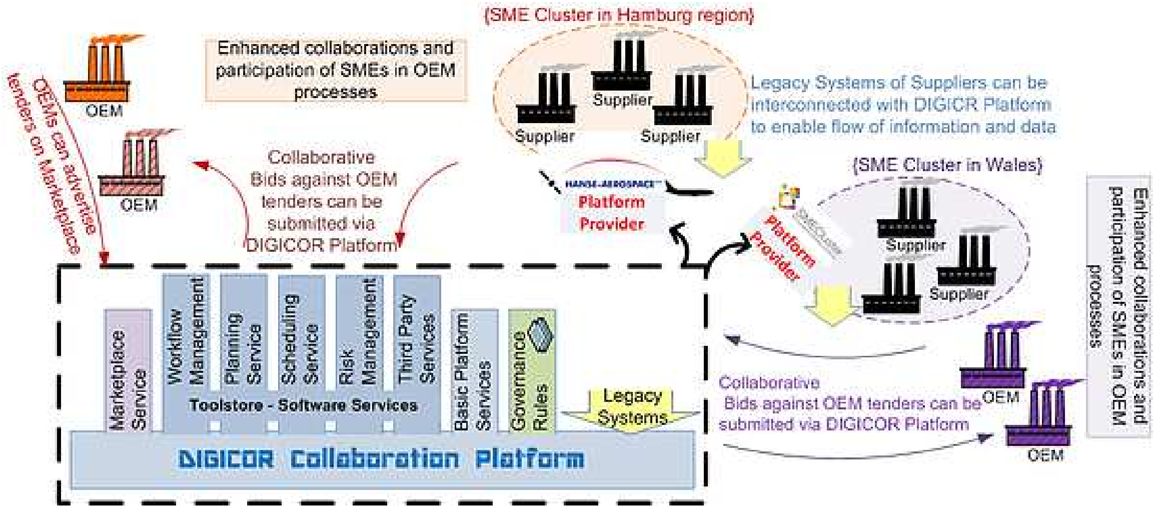


Figure 9. Conceptual architecture of DIGICOR Platform.

According to customer demands, novel features had to be developed and produced in very short time with close collaboration of OEMs and high-tech SMEs in an ad-hoc production / supply network. Both parties, the OEM and the innovative SMEs (organized in industrial clusters), were provided with supportive infrastructure such as technical platforms, novel governance approaches, IPR framework, coordination tools and services to simplify the setup and management of ad-hoc production networks.

The DIGICOR Platform provided essential coordination support to suppliers and OEMs along the complete collaboration process by utilising a secured **IT infrastructure** and a set of **software tools** for planning and controlling the production across the production network.

3.4.1.8.1 Relevance to OPTIMAI

Although the main objective of DIGICOR (to facilitate the collaboration between companies belonging to the same supply chain) is not aligned with the objectives of OPTIMAI, to do so, the DIGICOR platform provides a governance framework that specifies the model for knowledge protection within the platform. This point is of special interest to OPTIMAI to develop its Legal and Ethical framework. No OPTIMAI partners were involved in this project.

3.4.1.9 DISRUPT

DISRUPT is an EU-funded project under the topic of digital automation. This project aimed to spearhead the transition to the next-generation manufacturing by facilitating the vision of a "Smart Factory", which requires flexible factories that can be quickly reprogrammed to provide faster time-to-market responding to global consumer demand, address mass-customisation needs and bring life to innovative products.

Through DISRUPT, traditional automation pyramid will be disrupted by utilising the ICT capabilities to facilitate in-depth (self-)monitoring of machines and processes, **provide decision support and decentralised (self-)adjustment of production, and foster the effective collaboration of the different IoT-connected machines with tools, services and actors**. By doing so, the DISRUPT project allowed seamless communication of information and decisions from and to the plant floor and facilitate efficient interaction with value chain partners.

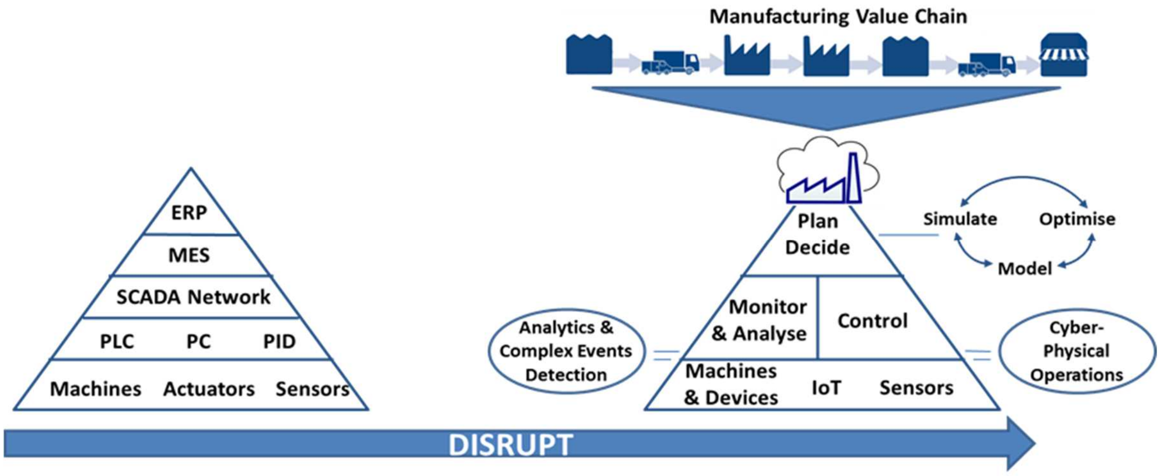


Figure 10. Conceptual Framework of DISRUPT.

The DISRUPT project set the following specific objectives:

- **Provide ICT support in manufacturing execution:** offer a multi-sided, cloud-based platform for large corporations and SMEs to optimize business goals.
- **Materialise ICT-enabled innovation in manufacturing:** unify automation hierarchy of IoT and CPS production systems under a seamless data-intensive modelling approach.
- **Implement modular, decentralized production topologies:** integrate Smart Objects into analytics, simulation and optimisation tools for efficient decision support in the context of plant's virtual production model.
- **Devise novel and coherent business models:** sustain individual strategies and visions of manufacturing companies and especially SMEs, while optimizing the entire manufacturing chain.

From a technological perspective, DISRUPT envisions each element of production to be controlled via the **IoT** by its virtual counterpart. The collected data will be analysed to detect complex events that trigger automated actions. By combining modelling, simulation and optimization, DISRUPT will enhance decision support over a secure and flexible **"plug and play" platform** that will allow engineers from different disciplines to collaborate in developing services. This cloud-based platform will eventually accommodate the anticipated high data volume and computational needs, while offering accessibility via any device anywhere in the world.

3.4.1.9.1 Relevance to OPTIMAI

To increase its flexibility and efficiency, factories need to be able to obtain information in real-time across physical production systems for better decision making. To this end, DISRUPT and OPTIMAI share a common objective: to manage data processing in an Industry 4.0 context. OPTIMAI could benefit from the integration and realization of data collection and knowledge management proposed in DISRUPT.

OPTIMAI can profit from the experience that DISRUPT project offered in the domain of machine and process monitoring, modelling, simulation and optimization through the employment of ICT tools, the enhanced utilization of IoT and the development of virtual models for certain production elements. These services will provide OPTIMAI with the ability to integrate such technologies and platforms into certain activities including among others augmented reality, predictive maintenance, IoT and digital twins.

3.4.1.10 FAR-EDGE

FAR-EDGE was a promising project to offer "**Factory Automation Edge Computing Operating System Reference Implementation"**. The main focus of the project was the adoption of decentralized automation architectures from manufacturers (including edge computing), which required mitigation of the following key challenges [16,17]:

- IoT/CPS implementation, deployments and standards still in their infancy.
- Lack of a well-defined and smooth migration path to distributing and virtualizing the automation pyramid.
- Lack of shared situational awareness and semantic interoperability across the heterogeneous components, devices and systems (including manufacturing CPS-based automation environments).
- Lack of open, secure and standards-based platforms for decentralized factory automation.

The migration from the conventional centralized control to IoT/CPS-based decentralized control -as offered by FAR-EDGE- is shown in Figure 11. **Technologies:** The project was highly involved in **IoT, Edge/Fog computing,** as well as **Distributed Analytics and Simulation**.

3.4.1.10.1 Relevance to OPTIMAI

OPTIMAI envisions to employ technologies like IoT, Cloud/Fog computing and decentralized processing (blockchain etc.). Thus, the experience of FAR-EDGE may be exploited to speed up preliminary research. On the other hand, since OPTIMAI strongly adopts AI-technologies, it may give feedback to FAR-EDGE as of how to upgrade the intelligence of its techniques by incorporation of AI.

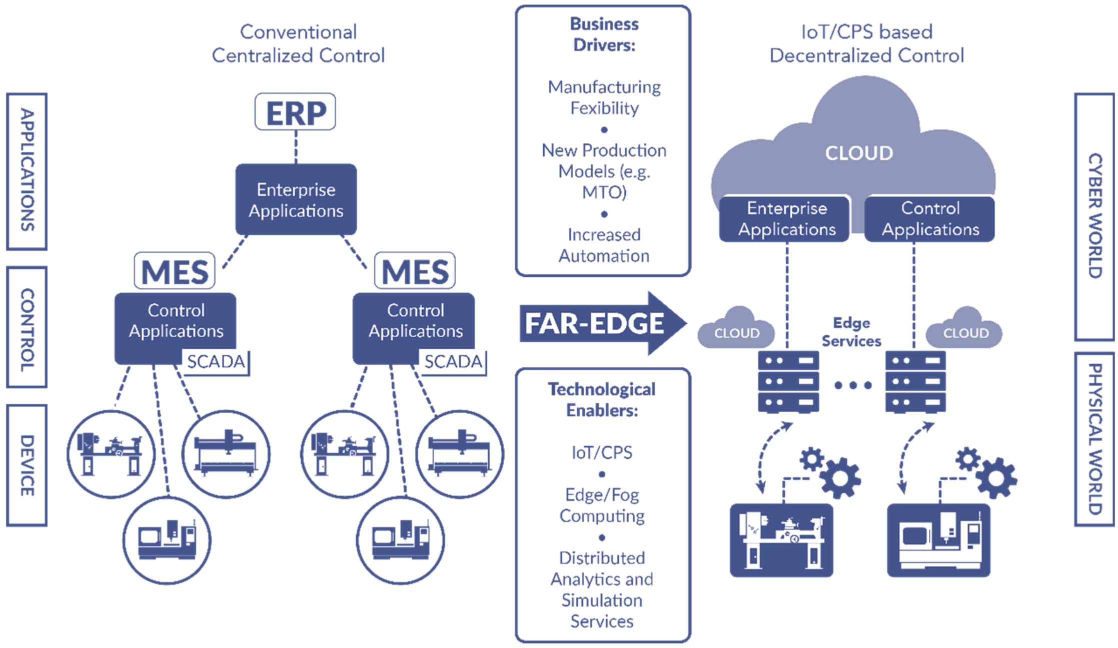


Figure 11. Migration from the conventional centralized control to IoT/CPS-based decentralized control within FAR-EDGE [16].

3.4.1.11 NIMBLE

NIMBLE was a FoF project to build a "**Collaboration Network for Industry, Manufacturing, Business and Logistics in Europe**" [18,19]. NIMBLE aimed to address 5 main escalating objectives:

- Develop the collaboration infrastructure with core services.
- Ensure Ease of Entry and Ease of Use.
- Grow the use of the platform.
- Master the platform and achieve higher maturity levels.
- Ensure Trust, Security, Privacy, Reputation and Information Quality.

NIMBLE actually targeted the development of the infrastructure for a **cloud-based**, Industry 4.0, **IoT-enabled** B2B platform on which European manufacturing firms can register, publish machine-readable catalogues for products and services, search for suitable supply chain partners, negotiate contracts and supply logistics, and develop private and secure B2B and M2M information exchange channels to optimize business workflows. The infrastructure was developed as an open-source software under **an Apache-type, permissive license**. The structure of NIMBLE is shown in Figure 12 [19].

3.4.1.11.1 Relevance to OPTIMAI

OPTMAI may benefit from NIMBLE by exploiting the experience gained in the areas of IoT, and Cloud Computing, which are key-ingredients to OPTIMAI. Of course, OPTIMAI is by definition expected to take these techniques to a higher level by incorporation of AI. No OPTIMAI partners were part of NIMBLE; but this can pave the way for new partnerships and collaborations.

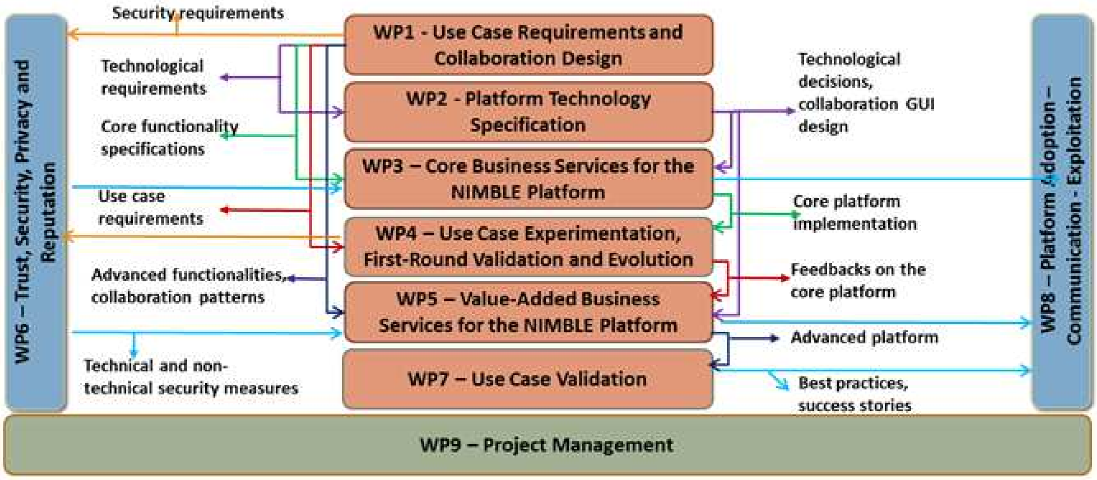


Figure 12. Structure of NIMBLE.

3.4.1.12 SAFIRE

The primary objective of the **SAFIRE** project (**Cloud-based Situational Analysis for Factories providing Real-time Reconfiguration Services**) was to develop cloud-based analytics and reconfiguration capabilities that provide:

- Both reactive and predictive reconfiguration for both production systems and smart products.
- Flexible run-time reconfiguration decisions during production rather than pre-planned at production planning time.
- Real-time reconfiguration decisions for optimisation of performance and real-time production and product functions

The advanced analytics and reconfiguration capabilities developed in SAFIRE based on mastering the **big data** challenges associated with manufacturing (sensor and process data), enterprise data and smart product data to provide advanced analytics that allow manufacturers to address production system behaviour forecasting and to establish optimisation methods that are integrated into the design and product chain. The SAFIRE infrastructure is shown in Figure 13 [20].

3.4.1.12.1 Relevance to OPTIMAI

OPTMAI and SAFIRE work both within the industry 4.0 framework, but seem to have different directions and goals. However, the **predictive analytics engine** of SAFIRE may be an asset for the development of predictive maintenance procedures of OPTIMAI, and even be used as comparisons baseline. Furthermore, **big-data** processing techniques may also be adapted to OPTIMAI activities. No OPTIMAI partners were part of SAFIRE; but this can pave the way for new partnerships and collaborations.

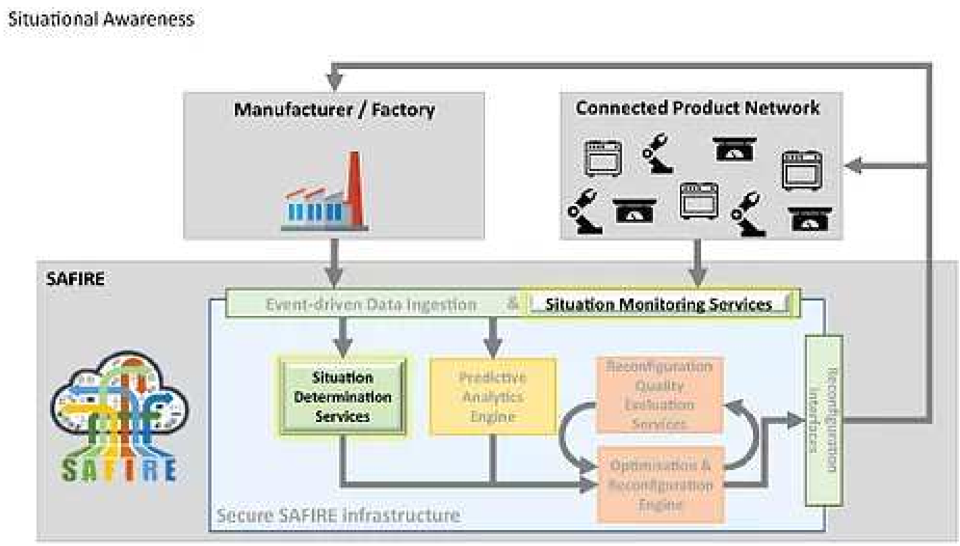


Figure 13. The infrastructure of SAFIRE.

3.4.1.13 VFOS

The **VF-OS** (Virtual Factory Operating System) was a FoF project that targeted the following key objectives [21]:

- Development of an Open Operating System (vf-OS) and Software Development Kit (OAK) for Factories of the Future that to be the reference system software for collaborative manufacturing and logistics processes including its associated resources and data.
- Development of an Open vf-OS Platform, including a Multi-sided application marketplace and development studio, to become the Apps Store for Manufacturing industry.

vf-OS was composed of a Virtual Factory System Kernel (vf-SK), a Virtual Factory Application Programming Interface (vf-API) and a Virtual Factory Middleware (vf-MW) for interoperable and **secure collaboration among supply networks, enterprises, machines, data and objects**. The technologies employed in VFOS as are shown in Figure 14 [22].

Figure 14. Technologies employed in VFOS.

3.4.1.13.1 Relevance to OPTIMAI

Although VFOS does not consider any AI enhancements, it employs numerous technologies that are also part of OPTIMAI, such as **Cloud Computing, Data Analytics, IoT** etc. Thus, OPTIMAI may take advantage of existing work and take it to a higher intelligence level by incorporation of AI technologies.

3.4.1.14 SCALABLE4.0

SCALABLE4.0 was about the development of **scalable automation for flexible production systems** [23]. The main objective of the ScalABLE 4.0 project was the development and demonstration of an open scalable production system framework (OSPS) that enables **optimization** and **maintenance** of production lines 'on the fly', through **visualization** and **virtualization** of the line itself; this practically means real-time decision making. This became possible by integrating enterprise information systems, automation equipment and open APIs for system optimization. The concepts of SCALABLE 4.0 is shown in Figure 15 [24].

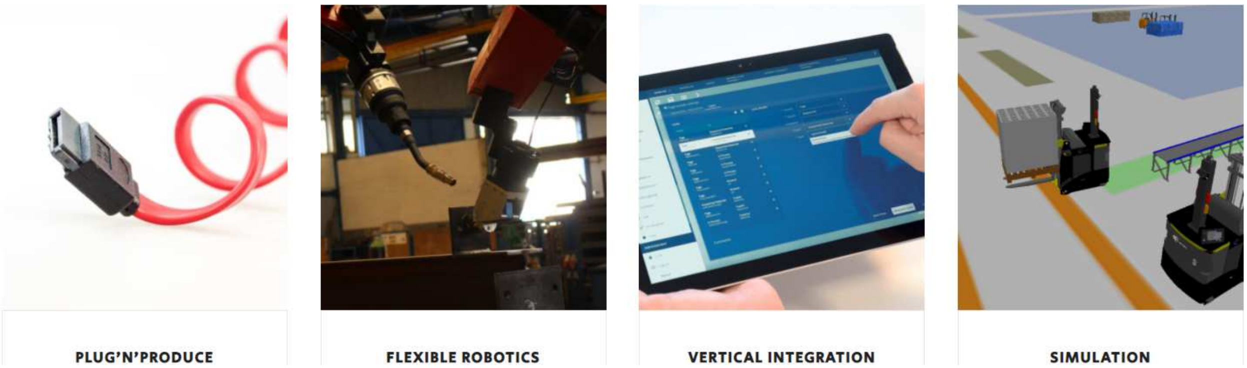


Figure 15. Concepts of SCALABLE 4.0.

3.4.1.14.1 Relevance to OPTIMAI

The work made in SCALABLE4.0 may be exploited by OPTIMAI as well. Optimization and maintenance may be enhanced by AI and be included in OPTIMAI's predictive maintenance, quality control and zero-defect manufacturing. Furthermore, visualization and virtualization may provide feedback for OPTIMAI's AI-enhanced digital twins and augmented reality.

3.4.2 Projects focused on quality control and zero-defect manufacturing

The mainly focused areas of zero-defect manufacturing concept are to avoid completely the defects in a production environment, to reduce faults and cost. It is important to increase productivity, competitiveness, as well as a higher resource and energy efficiency.

In what follows, the selected European projects that belong to EFFRA (European Factories of the Future Research Association) are presented that focus on Zero-defect manufacturing.

3.4.2.1 QU4LITY

QU4LITY stands for an **"Autonomous Quality Platform for Cognitive Zero-defect Manufacturing 4.0 Processes through Digital Continuity in the Connected Factory of the Future".** It is a European project implemented within Industry 4.0 and dealt with autonomous quality and zero-defect manufacturing. This project implemented autonomous ZDM strategies in automotive, aeronautics, railways, etc. QU4LITY exhibited an open, certifiable and highly standardized shared data-driven ZDM product and service model for Factory 4.0. It developed 5 strategic ZDM plug & control lighthouse equipment pilots and 9 production lighthouse facility pilots in a realistic and replicable way. The main objective of this work was the development of an open platform autonomous ecosystem, to achieve zero-defect across all phases during production and process lifecycle of SMEs. Among the most important outcomes of this project were the improvement of manufacturing, the enhancement of time decision making, as well as the elimination of the gap between predicted and real production process [25–28].

As depicted in Figure 16, it represents a ZDM production model for smart industry in a realistic way, focusing on operational and energy efficiency, defects elimination, as well as customer experience.

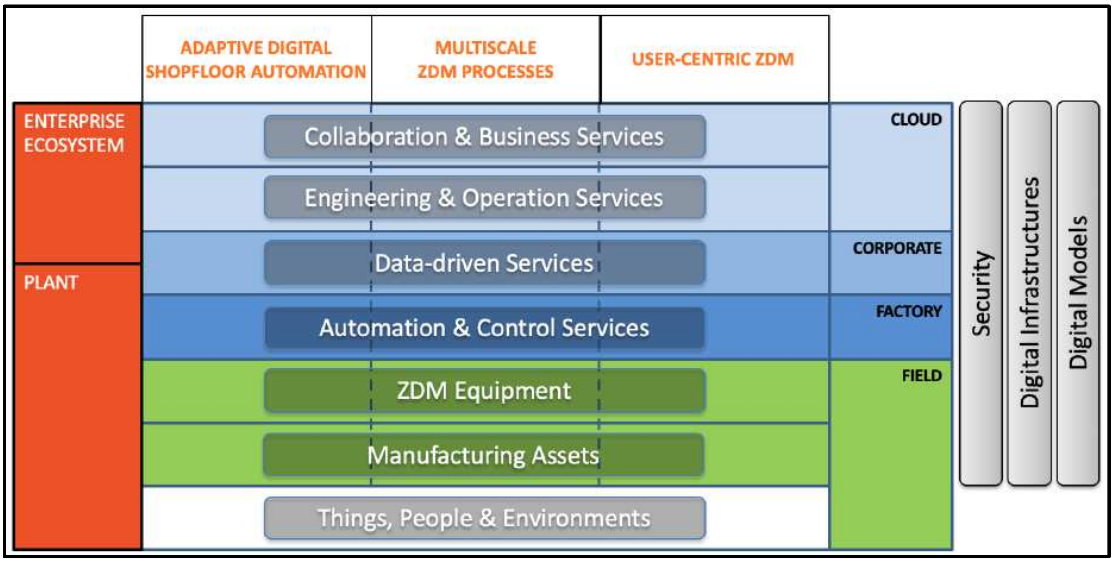


Figure 16. QU4LITY's framework overview [26].

3.4.2.1.1 Relevance to OPTIMAI

Under QU4LITY, VIS will provide the simulation models which will be further extended for the training of AI systems according to the OPTIMAI requirements.

In addition, under QU4LITY, ENG developed and integrated a range of digital enablers which supported the QU4LITY autonomous quality paradigm, as well as performed the tasks regarding the Reference Architecture, Open APIs and Blueprints for Autonomous Quality Solutions. Hence, being a strong ICT solution provider, ENG will bring its expertise on the project in the fields of data analytics and visualization, 3D modelling and simulation, software development and integration activities.

Particularly, for the metrology domain, in QU4LITY, the case is focused on enhancing industrial machines with measurement solutions, including hardware and software metrology systems, as well as its digital automation definitions. UNIMETRIK is a technology provider deploying a related solution in one of the demonstrators. UNIMETETRIK Role in QU4LITY concentrates on the definition and development of machine measurement solutions. This will include hardware and software metrology systems. It will bring its expertise in the digital automation definitions.

3.4.2.2 ForZDM

ForZDM stands for "**Integrated Zero-Defect Manufacturing Solution for High Value Adding Multi-Stage Manufacturing systems"**. The aim of this project was the development and demonstration of tools to support the rapid deployment of ZDM solutions in industry. The ForZDM project integrated multi-level system modelling, big data analysis, CPS (Cyber Physical Systems) and real-time data management to deliver an innovative ZDM methodology for the purposes of production and quality control of multi-stage manufacturing systems. This methodology was implemented and validated in manufacturing of jet engine shafts, medical microcatheters and railway axles.

The reference architecture of this project is shown in Figure 17 and consists of:

- **Data Acquisition System** which gathers and synchronizes all data of production line, such as materials quality data, process data, machine state data, production flow related data.
- **Data Management Platform** which stores updates and extracts features to be analyzed further.
- **Data Correlation System** which correlates the information between production process and resource data.
- **Error Budgeting and Root Cause Analysis tool** which characterizes the defect correlations in different production stages.

This approach dealt mainly with the diagnosis of defects by using preventive and corrective mechanisms with real-time control actions. The main result of this work was to achieve near zero defect manufacturing, emphasizing on the production of high-value and high-performance parts [29,30].

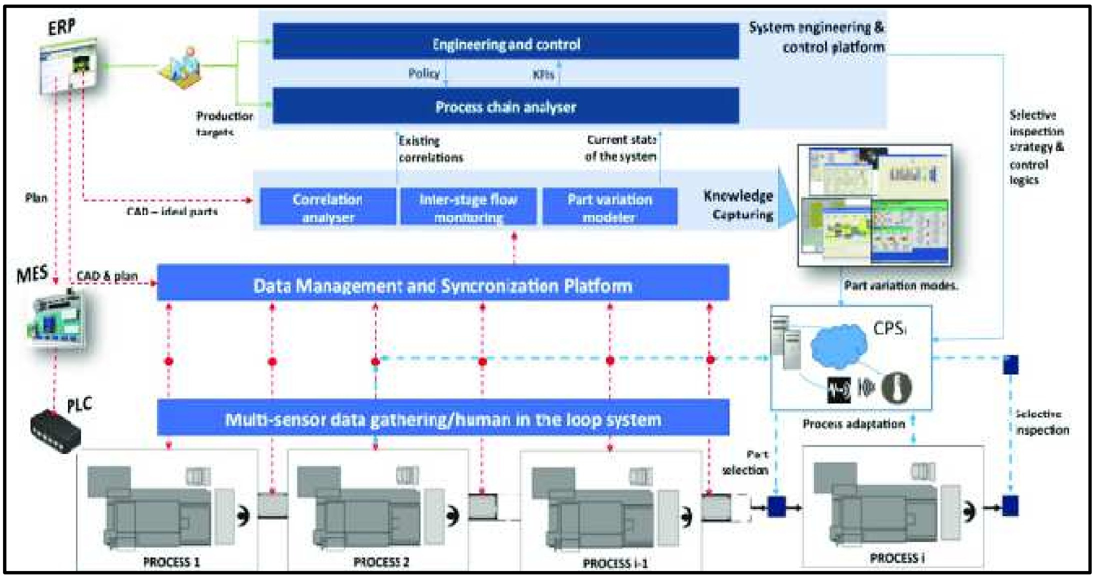


Figure 17. The ForZDM architecture [29].

3.4.2.2.1 Relevance to OPTIMAI

No partners were involved in this project.

In OPTIMAI, we will consider the methodologies used for data correlation, as well as machine learning-based analysis for zero-defect manufacturing.

3.4.2.3 STREAM-0D

STREAM-0D stands for **"Simulation in Real Time for Manufacturing with Zero Defects"**. This project aimed to accomplish zero defect production, by reducing the produced products variability and increasing the production flexibility, through an innovative control system integrated into production lines. The specific characteristics of products, such as dimensions and construction materials may differ between the production lines of an industry. That makes the whole production prone to faults and misleading, negatively affecting the flexibility of production flow, duration and eventually the quality of products. This task is what STREAM-0D managed to resolve. By using multi-physics simulation models, fed with real time measurements data, it enabled the prediction of product quality. Through the use of these models, workers could control the crucial steps of production in order to adjust the product to the exact design specifications. Some of the state-of-the-art technologies employed are shown in Figure 18.

This project was based on constant analysis, real-time supervision and monitoring of production line, predictive maintenance, as well as continuous training of their operators. Its main objective was to enable industries to modify their manufacturing processes in real time, introducing smart decisions based on prediction models. As a result, the production efficiency was enhanced, whereas time and money were saved [31].

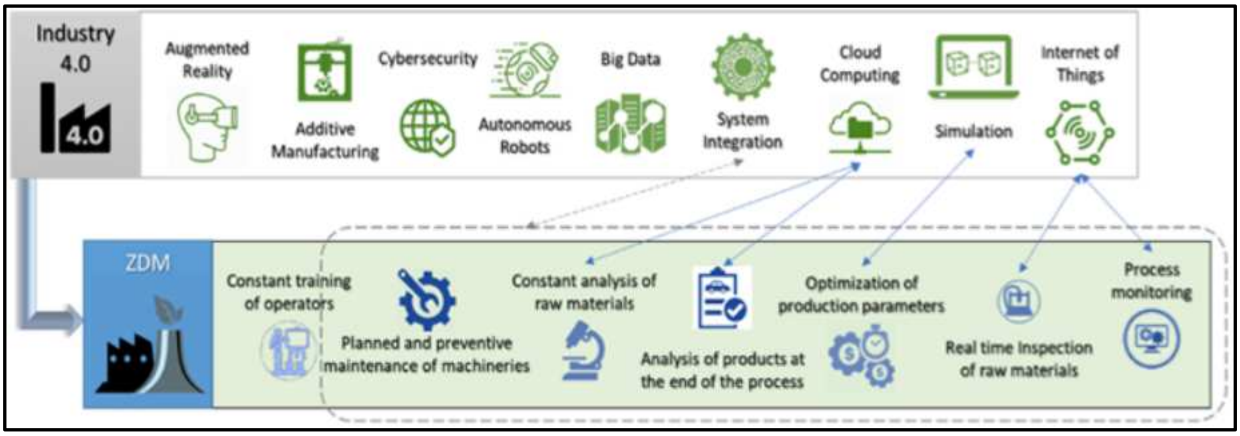


Figure 18. The STREAM-0D's framework [31].

3.4.2.3.1 Relevance to OPTIMAI

No partners were involved in this project.

In OPTIMAI, some of the state-of-the-art technologies in real time inspection of raw materials will be investigated focusing on ZDM. As in the case of the STREAM-0D project, OPTIMAI aims to increase the productivity of manufacturing procedures via the reduction of rejected parts and the control of the process. That could be accomplished through the implementation of real-time monitoring systems on specific machine tools to adjust online the manufacturing parameters increasing that way the performance of the production. Furthermore, the development of forecasting models in order to enhance the production efficiency coupled with high savings in costs and times in manufacturing procedures are some of the common strategies applied in OPTIMAI and STREAM-0D.

3.4.2.4 Z-Fact0r

Z-Fact0r was a promising project to offer "**Zero-defect manufacturing strategies towards on-line production management for European factories"**. This solution, as depicted in Figure 19, was composed of five multi-stage production-based strategies, targeting (i) the early detection of the defect (Z-DETECT), (ii) the prediction of the defect generation (Z-PREDICT), (iii) the prevention of defect generation by recalibrating the production line, as well as defect propagation in later stages of the production (Z-PREVENT), (iv) the reworking/remanufacturing of the product, using additive and subtractive manufacturing techniques (Z-REPAIR) and (v) the management of the aforementioned strategies through event modelling, KPI monitoring and real-time decision support (Z-MANAGE) [32,33].

Each presented strategy was activated based on the nature of the detected fault; each fault reduces production quality, creates defects, and increases expenses to the company. This holistic approach results predictions were above 95% of success. The main result was the development of a multi-parametric model along with the early-stage decision support system for inspection and control of production. Further achievements included the development of data-driven techniques for fault detection and fault tolerant control, the development of the early-stage inference engine, monitoring system deployment and sensor data mining, as well as the overall system integration.

Technologies: Defect prediction algorithms have been developed and finalized that allow the adjustment of manufacturing parameters in order to prevent defects.

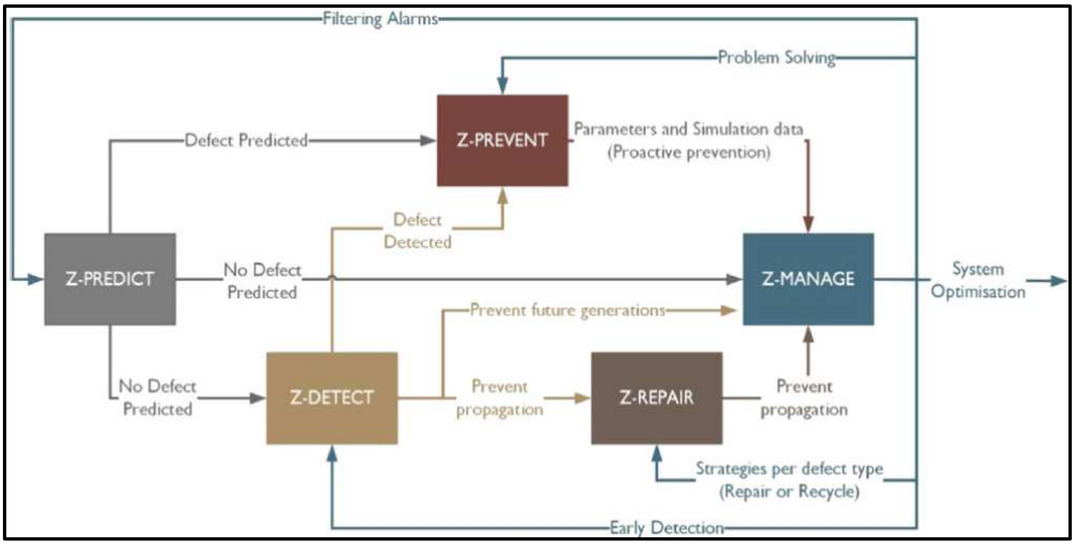


Figure 19. The Z-FACT0R's strategies architecture [33].

3.4.2.4.1 Relevance to OPTIMAI

Under Z-Factor CERTH developed the multi-parametric models along with the early-stage Decision Support System for inspection and control, and contributed to the design, in the middleware and semantic components' deployment, and system integration. These can be used as reference within OPTIMAI for the development of data-driven techniques for fault detection and fault tolerant control, the development of the early-stage inference engine, monitoring system deployment and sensor data mining, as well as the overall system integration. In addition, under Z-Factor, MSL acted as end-user and use case owner, and it collaborated effectively with CERTH.

Microchip Technology, formally Microsemi (MSL), as end-user, will provide his previous experience in OPTIMAI, focusing on detecting defects, analyzing their causes and predicting emerging deficiencies in deficiencies in the manufacture of electronic assemblies. The OPTIMAI project will add to the technology adopted from the Z-Fact0r project of which Microchip Technology was a partner. This has been expanded towards OEE and machine health checking and will be further expanded to cover the processes that form part of the Microchip Technology use cases in this project.

In this project, one of the companies of Innovalia Metrology strategic association, of which UNIMET is part, deployed and implemented digitalization technologies in different use cases to virtualize components and analyze dimensional information regarding them. This experience can be used as knowledge for certain scenarios of OPTIMAI pilots where it is required and feasible to perform this kind of studies.

3.4.2.5 GO0DMAN

GO0DMAN stands for "**Agent Oriented Zero Defect Multi-Stage Manufacturing**". This project aimed to integrate and combine process and quality control of multi-stage manufacturing productions (i.e., industrial sectors such as automotive, household appliance and semiconductor manufacturing) into a distributed system architecture constructed by an agent-based CPS and smart inspection tools designed to apply ZDM strategies. This architecture is depicted in Figure 20, and is composed of:

- **ZDM knowledge management** to contain all information of the knowledge space and correlate analytic results with human interpretation.
- **ZDM data analytics** to detect faults in manufacture at an early stage and try to prevent them from happening.
- **Multi-Agent system** to manage distributed and autonomous intelligent agents in different production areas, which cooperate allowing the distributed data collection and real-time decision making.
- **Smart inspection tools** acting as the CPS that collects measurements and performs diagnosis tests during manufacturing.

In this project, promising Machine-Learning and Multi-agent Systems were adopted to enable and manage intelligent environments concerning the Internet of Things. A new approach based on cloud, Edge and Fog computing was delivered for the development of a decentralized multi-level data analysis computing infrastructure that supports industrial CPS. In industry, new data models were proposed and deployed incorporating the interoperability and interconnectivity among heterogeneous production components as well as a variety of interlinking elements within the shop-floor. The proposed data models representing the GO0DMAN solution, integrate all the information required for the reduction of the defects, the evaluation of the respective causes and the tailoring of suitable strategies to avoid the propagation along the line, in the most efficient way. This project's goal was the overall quality and industrial productivity improvement, providing a ZDM system architecture in various industries [34,35].

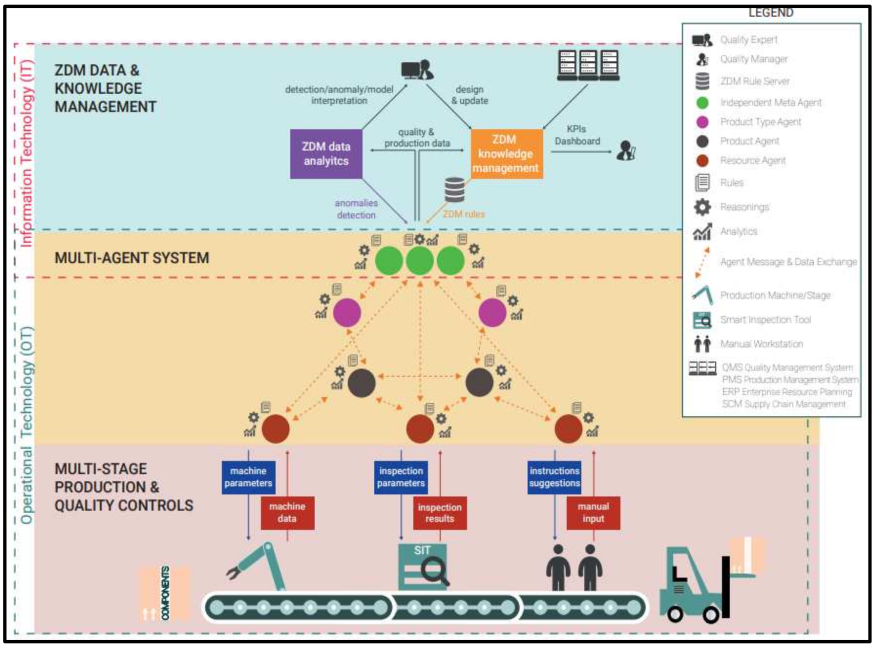


Figure 20. The GO0DMAN distributed system architecture [35].

3.4.2.5.1 Relevance to OPTIMAI

The investigated AI approaches considering Cloud, Fog and Edge computing in a distributed environment, will be further investigated to handle many industrial scenarios, and support the development of industrial CPS. Also, the new solutions regarding the interoperability and interconnectivity among heterogeneous production components will be further investigated and adopted where they will be effective. Furthermore, AI-based models will be developed within the OPTIMAI project where the goal is to achieve early defect-detection of the manufacturing components. As in the case of the Go0DMAN project, these models will be tested in real case scenarios in industry to identify various defects and correct them prior to the termination of the manufacturing process.

3.4.2.6 IFaCOM

IFaCOM stands for "**Intelligent fault correction and self-optimizing manufacturing systems".** Production strategies were developed in three different levels: i) closed-loop control of process parameters, ii) medium-time process tuning and iii) long-large performance improvement; these levels are depicted in Figure 21. This project approach relied on intelligent sensing and monitoring systems, which supervised production process, and applied decision making for a high-level product quality. A virtual demonstrator was developed for defect diagnosis and prognosis, based on fuzzy logic algorithms; the system could detect faults in production, based on the input parameters [36,37].

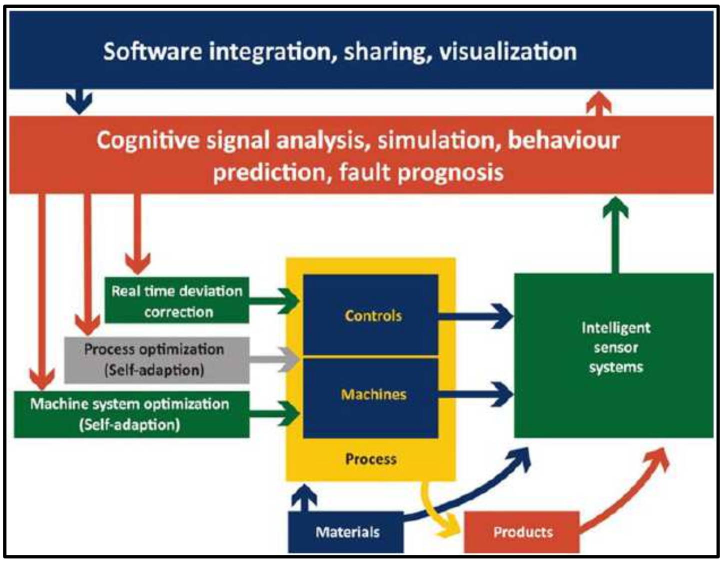


Figure 21. The IFaCOM architecture [36].

The main objective behind this project was to reduce all sources of variation, and to develop a method to eliminate the detrimental effects of unavoidable variance in material, part and processes quality that is the major source of defects in many manufacturing processes.

The results among others, include i) the definition, developing, implementation and validation of a Simulation-based, Intelligent Fault Diagnosis and Prognosis System for Optimization over time, ii) the development of an intelligent self-adaptation and self-optimization methodology which relies on fuzzy logic (which has the ability to account for vagueness/imprecision and nonlinear behavior, which are common characteristics to manufacturing processes and systems) for part quality prediction, fault diagnosis and process parameters adjustment suggestions, iii) the establishment of sensor systems solutions and strategies for the real-time assessment of the status of the manufacturing system, the manufacturing process and the part during operation.

3.4.2.6.1 Relevance to OPTIMAI

No partners were involved in this project.

The IFaCOM approach which relied on intelligent sensing and systems monitoring will be investigated in OPTIMAI with a view to enhancing the capabilities of the project for quality control and ZDM. Methods and techniques applied in IFaCOM project such as closed loop control of vital parameters or suitable measurements could potentially be utilized in OPTIMAI to restrain the propagation of defective parts along the production phase. Once data starts coming in from the OPTIMAI systems for data gathering this would then need to be assessed as to usefulness and effectivity.

3.4.2.7 ZDMP: Zero Defect Manufacturing Platform

ZDMP stands for **Zero Defect Manufacturing Platform** [38,39] and aims at providing an extendable platform for supporting factories with a high interoperability level to cope with the concept of connected factories to reach the **zero defects** goal. In this context, ZDMP will allow end-users to connect their systems (i.e. shopfloor and ERP Systems) to benefit from the features of the platform. It provides Process and Product **Quality** support on top of a platform layer.

ZDMP is a platform which consists of a suite of components that deploys and enables the ecosystem. The main functionalities of the platform are: (i) To build applications that monitor, manage, and control connected devices, (ii) To collect and analyse data from connected devices.(iii) To enable secure connectivity and privacy between devices and throughout the platform, (iv) To manage interconnectivity from device/sensors, to machines, to factories, to partners, (v) To offer core API services to facilitate use, (vi) To allow integration with 3rd party systems/services and provide interoperability with other platforms, (vii) To automate and provide services for the intelligent Zero Defects ecosystem of the platform.

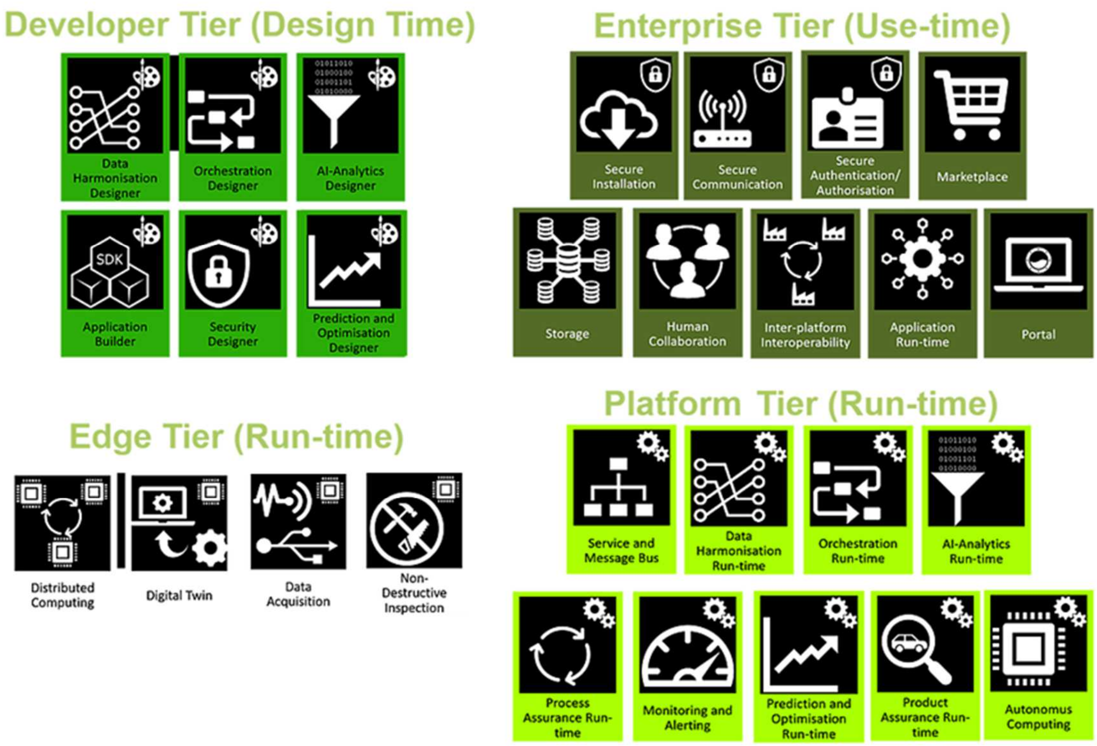


Figure 22. The ZDMP technologies architecture.

Focusing on the **Zero Defects** concept, ZDMP aims at supporting both process and product quality assurance in dedicated workstreams. The **Prediction and Optimisation** component supports these features for different aspects of manufacturing process, both during the preparation and the production stage. Optimisation largely relies on numerical methods to reduce changeover times, eliminate related errors, or keep process quality within a certain range. Additionally, predictor components rely on machine learning methods that provide prognostic models that predict future trends of the process quality to support decision making during operation.

The **Digital Twin** component is a digital representation of the current state of a manufacturing process and the characterisation and modelling of product features (physical characteristics, bill of materials, tolerances, etc), which provides data objects that describe different aspects of the physical and logical parts of a manufacturing process, including the status of the different (potentially distributed) components of the manufacturing system and product features.

3.4.2.7.1 Relevance to OPTIMAI

The goal of OPTIMAI and ZDMP are zero-defect manufacturing and increased product quality. Apart from this, they both share common aspects and technologies like big-data processing, prediction and optimization, use of digital twins etc., with OPTIMAI focusing on the integration of AI technologies. Since ZDMP has a head start, it can lead the way in the areas of common interest and then OPTIMAI may benefit from gained experience to introduce AI-upgrades. Joining forces of these two projects will be beneficial for European smart factories.

3.4.2.8 KYKLOS 4.0

KYKLOS 4.0 is the acronym for "**Advanced Circular and Agile Manufacturing Ecosystem based on rapid reconfigurable manufacturing process and individualized consumer preferences"**. The project aims at providing an Ecosystem which creates and supports the configurations, methodologies, production techniques, decisions and actions at all different levels and stages of the equipment manufacturing value chain. The purpose of this concept is the development of a CPS and AI technologically based innovative circular manufacturing ecosystem. This project is focused on enhancing energy efficiency and reducing raw material and time waste through to the second use of parts or material (including waste from manufacturing process). It also aims at applying a customer-centric approach, by producing personalized products with extended life cycle and on-demand manufacturing and best meet the Industry 4.0 objectives of operational excellence. KYKLOS 4.0 will deliver an advanced configuration variants' framework and state-of-the-art production paradigm, embedding key technologies into a unified platform ecosystem to manage live product innovation, via building and shipping "configuration to specification", through the seamless adaptation on new customer requirements. This involves a set of intelligent tools for real-time analytics and prediction, and recommender systems, further integrated into KYKLOS 4.0 configuration environment.

In relation to the range of circular and flexible manufacturing aspects the KYKLOS 4.0 Ecosystem will provide a set of self-organizing, data driven modules (able to work independently) which will trigger dynamic interaction between them, and a smart orchestrator which will provide the ability to exchange customized product information between involved actors in the product life cycle, to dynamically handle any necessary production line changes (needs for energy and raw materials, fast reconfiguration and re-use) given a superior proficiency to tackle the varieties of personalized products and to deal with personalized product design issues and perform quality focusing on the extension of Product End of Life.

The collaborative platform of this project is depicted in Figure 23. A virtual marketplace contains all the available services from different factories included in it, giving users the ability to set their requests, monitor the status of services, receive recommendations, obtain early diagnosis by AI software, etc. [40].

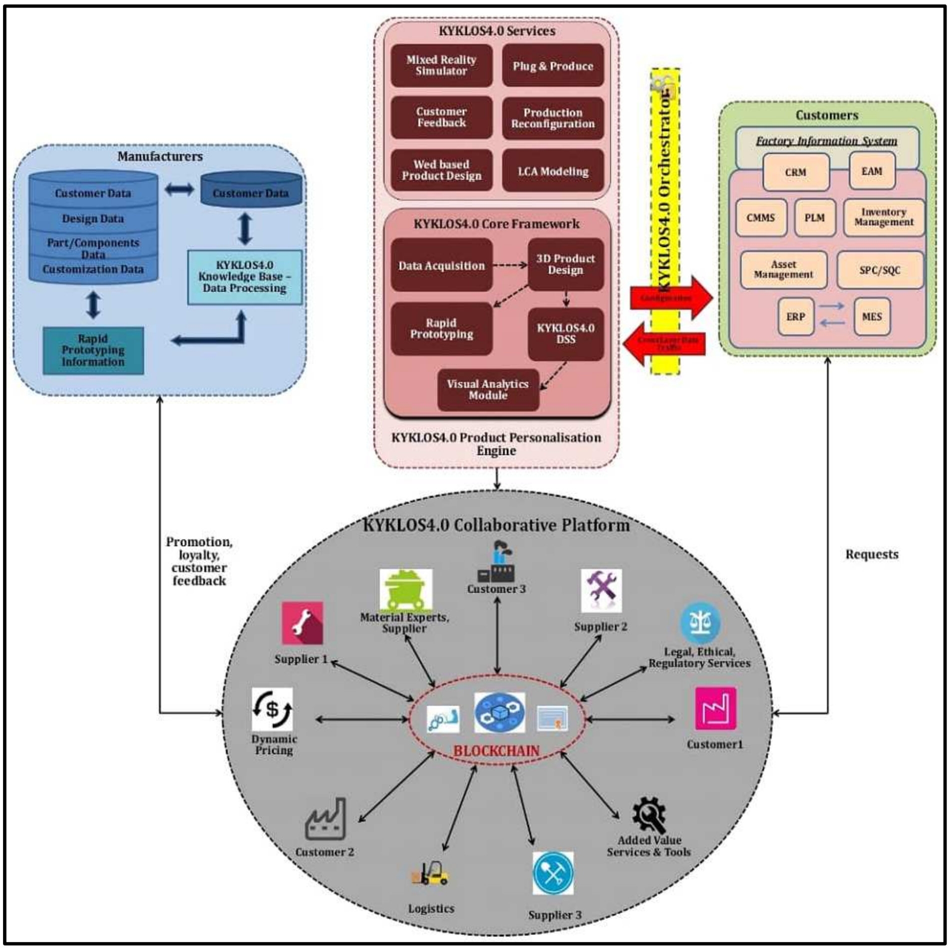


Figure 23. The KYKLOS 4.0 collaborative platform [40].

The main result of this project will be the creation of favourable conditions for the rapid reconfiguration of manufacturing process, in order to continuously follow Circular Manufacturing Framework and the individualised consumer/customised products demands.

3.4.2.8.1 Relevance to OPTIMAI

CERTH is a partner in KYKLOS contributing to tasks related with Data Reduction Techniques & Fault Dependency on the production line, as well as with production equipment clustering. Advanced machine learning and deep learning algorithms will be exploited and deployed to develop an intelligent framework towards Prognostics and Health Management (PHM) at a component level, and process diagnostics with the ability of following up the overall system's health status, by relying on time-dependent condition-based features or indicators.

The ML and deep learning approaches will be further investigated, exploiting parameter selection and regularization and applied in OPTIMAI for the development of AI components to perform quality control toward zero defect manufacturing.

3.4.3 Projects focused on AI-enhanced Digital Twins

3.4.3.1 PreCoM

PreCoM stands for "**Predictive Cognitive Maintenance Decision Support System**". The project targeted a smart maintenance decision support platform, able to identify and locate faults in production. In particular, the project objectives were the deployment and testing of a predictive cognitive maintenance decision-support system whose capabilities include the: identification of damage, assessment of damage severity, prediction of damage evolution, estimation of remaining asset life, reduction of the possibility of false alarms, more accurate failure detection and ultimately the increase of the in-service efficiency of machines.

It could estimate the total damage caused to the production and predict the propagation of this damage in the industry. This system was able to estimate the remaining life-time of industrial machinery and notify the production for any needed maintenance [41]. As shown in Figure 24, the construction of this system contains:

- **Data acquisition module** which includes all the sensors and actuators used to monitor machinery health.
- **AI module** which can estimate machinery health condition, using data analytics and ML algorithms.
- **Secure integration module** which provides connectivity and security in the implemented systems, via a private cloud.
- **HMI module** which includes all the ways of machinery and production handling.

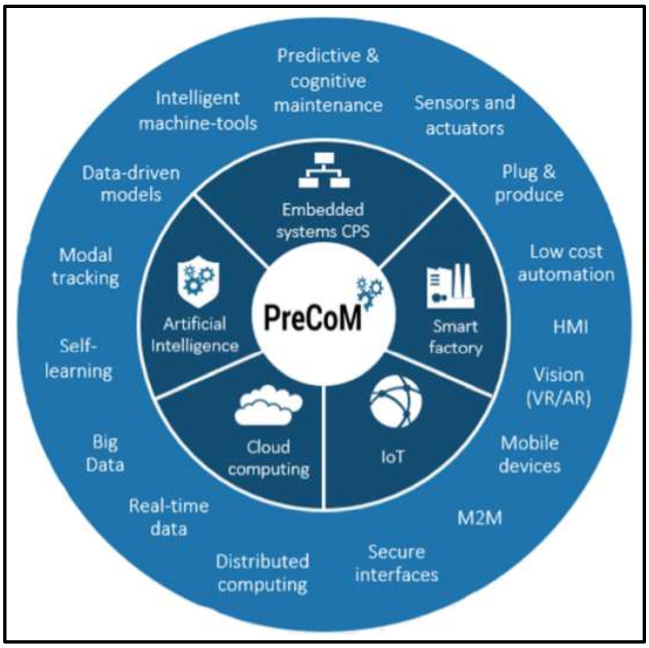


Figure 24. PreCoM's architecture [41].

The main result of the project involves the implementation of this decision-support system which achieved an improvement in production, as well as a decrease in the waste of energy and materials consumption, a reduction in faults and accidents rate etc. More specifically, the project demonstrated a direct impact of the platform on maintainability and availability (an increase by 15%), work safety (a reduction of failure-related accidents by 30%) and costs (reduction on energy consumption by 6-10% and on raw material consumption by 7-15%). The results of the project were documented in detailed business cases for widespread industry dissemination and exploitation.

3.4.3.1.1 Results relevant to OPTIMAI

No partners were involved in this project.

The proposed AI modules in DSS will be considered in OPTIMAI to enhance the intelligent capabilities of the project by deployed AI modules on the edge that will; i) optimize data acquisition through dynamic parameter calibration for improved accuracy and precision; and ii) provide an initial data processing layer for facilitating data exchange and further analysis. Moreover, both projects aim to develop and deploy a predictive maintenance decision-support system in order to identify and further localize the damaged parts during the production stage. The accurate failure detection as well as the adjustments of the manufacturing conditions during the construction of the part could potentially lead to the increase of the performance of the employed machine tools.

3.4.3.2 FORTISSIMO 2

FORTISSIMO 2 [42] was the second part of the project named "**Factories of the Future Resources, Technology, Infrastructure and Services for Simulation and Modeling**". It aimed to enhance competitiveness of EU industries by providing advanced computing cloud services. Exploitation of high programming modelling and analytics led to an increase of quality in products and services in both small and medium enterprises. There are plenty of SMEs case studies where FORTISSIMO 2 gave solutions. Some of them are listed below:

- **Optimization of the anaerobic digestion process for biogas generation**. A computational model was employed to simulate digesters' function and optimize the biogas energy balance.
- **Predictive diagnosis services for the automotive industry.** A system was developed to predict failures and mechanical problems by analyzing sensorial data. Results were employed to redesign automotive parts and apply modifications in maintenance.

The outcome of this project was the development of a Fortissimo marketplace (Figure 25), that provides alternative/advanced models and tools via its operational high performance cloud infrastructure [42].

3.4.3.2.1 Results relevant to OPTIMAI

No partners were involved in this project.

The computing cloud services and high performance infrastructure implemented by FORTISSIMO 2 will be considered as a useful tool for OPTIMAI to further enhance the capabilities of the intelligent marketplace which will be implemented sharing AI models between industries for common tasks such as surface inspection. Additionally, the benefits of HPC cloud-based advanced modelling, simulation and data analytics will be properly exploited by OPTIMAI and will support planning, implementation and realization of the project's objectives.

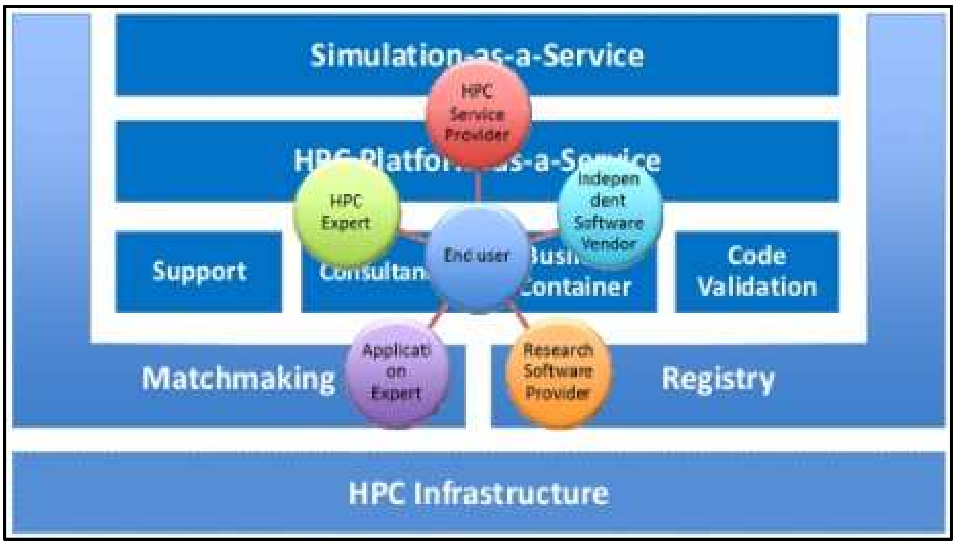


Figure 25. Marketplace services of FORTISSIMO2 [42].

3.4.3.3 DATAPORTS

DATAPORTS a.k.a. "**Data Platform for the Connection of Cognitive Ports**" used several state-of-the-art technologies to implement smart and cognitive ports between countries (Figure 26). It targeted the development of an industrial data cognitive platform, with a focus on the empowerment of data management for cognitive services in logistics and transportation companies. DataPorts was implemented in EU ports so as it is connected with existing digital systems and interacts with them providing information and data exchange. DataPorts enabled new services, advanced AI-based and data-driven business models, as well as cognitive applications. The platform can connect and unify all the digital seaports into an integrated ecosystem. DataPorts also enabled a secure data trading base, and by applying smart integrated AI systems, it improved the port value chain. It also provided a reliable and efficient way of business management that will strengthen the EU Single Market [43].

3.4.3.3.1 Results relevant to OPTIMAI

Under DATAPORTS, CERTH contributed to Data governance and Distributed Ledger Technologies (DLT) supported interoperability for transportation, logistics and monetization of data. These technologies will be adopted to the architecture of OPTIMAI. DLT will provide a decentralized solution for real-time validity and traceability within an actual production line. DLT or Blockchain tools will be employed in the frame of the OPTMAI project in order to ensure the security of the firmware along the industries and the applied sensors as well as to verify the integrity of the AI models that will be utilized for several sensor measurements.

UPV is co-Technical Coordinator in DATAPORTS. Its main role is to design the data platform in which transportation and logistics companies around a seaport will be able to manage data like any other company asset, to create the basis to offer cognitive services.

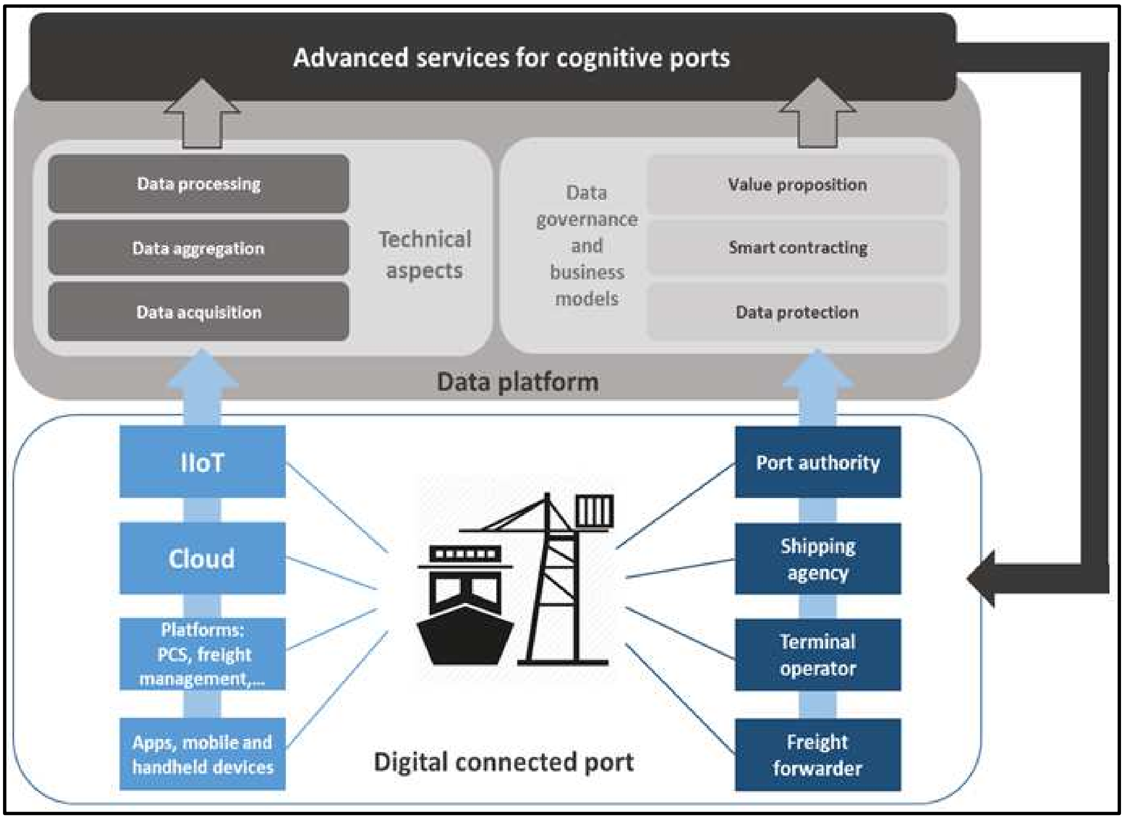


Figure 26. DATAPORTS architecture [43].

3.4.4 Projects focused on Computer Vision and Augmented Reality

3.4.4.1 SERENA

SERENA which stands for **"Versatile plug-and-play platform enabling remote predictive maintenance"** was focused on the development of a new design and implementation of predictive maintenance technologies, in order to enhance operating life of manufacturing systems. The purpose of this project was to provide advanced AI methods for predictive maintenance, AR-based operations for local maintenance support, as well as IoT systems for data collection of future industry.

The aim of SERENA project is to build an Intelligent Manufacturing System able to improve manufacturing processes taking into account data gathering on the factory floor. SERENA proposed a solution based on a) remote access and data processing in cloud for predicting maintenance actions, b) advanced IoT system and smart devices for data collection and monitoring of machinery conditions, c) artificial intelligence and hybrid methods for predicting potential failures and improve process-related parameters d) AR based technologies for providing real-time animation and indications for a maintenance operator.

The SERENA methodology is presented in Figure 27 [44,45]. The results of SERENA platform include the simplified maintenance and improved productivity in manufacturing process after a reduction in production times and expenses. Specifically, an increased in-service efficiency was achieved (by 10%) by reducing the failure rate, maintenance time and unexpected manufacture outage. More predictive maintenance was adopted as a result of the demonstration of more accurate, secure and trustworthy techniques at component, machine and system level. Also, an increased accident mitigation capability was attained.

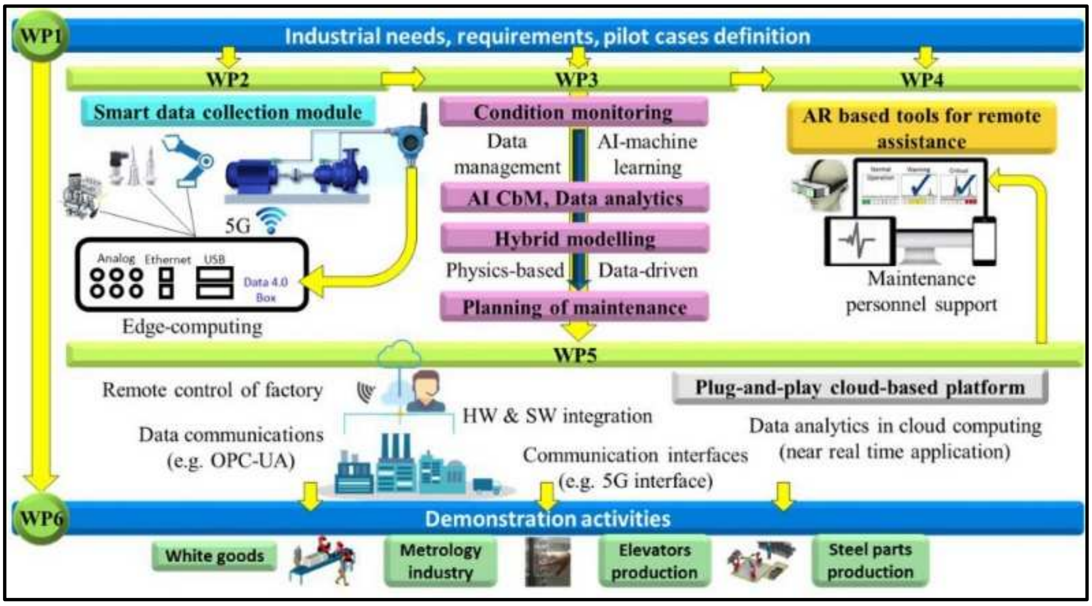


Figure 27. SERENA project methodology [45].

3.4.4.1.1 Relevance to OPTIMAI

In SERENA Project, ENG was playing a key role in the implementation of the secure hybrid edge-cloud platform for remote maintenance. ENG was also responsible for industrial exploitation activities and for bringing the project results closer to the market. Therefore, ENG will transfer the experience and expertise from this project and will contribute to the development of OPTIMAI security middle box as well as in the activities related to Blockchain framework for traceability and data integrity.

Additionally, as shown in Figure 27, one of the demonstrators was related to the metrology industry, led by TRIMEK, one of the companies included in Innovalia metrology strategical association, as is the case for UNIMET. In this use case, several SERENA services were deployed, including remote machine monitoring systems and data analytics, whose outcomes can be used as experience for the metrology implementations in OPTIMAI project.

3.4.4.2 PREVISION

PREVISION (H2020-FCT-03-2019) stands for "**Prediction and visual intelligence for security information**". The aim of this project was the development of a big data platform, to provide crime analysts and investigators with advanced techniques against cybercrime, and criminal/terrorism acts. The architecture of this work (Figure 28) was based on modules such as visual intelligence and data mining modules for cyber-criminal activities prevention and investigation.

This platform could handle, manage and analyze in near-real-time massive web data streams, in order to build dynamic information graphs that represent criminal interrelations. Humanitarian sciences were combined with data science models and techniques, like advanced behavioral analytics, near-real-time analysis, ML techniques for abnormality detection etc. A major contribution of this project was the cross-border security protection against crime [46].

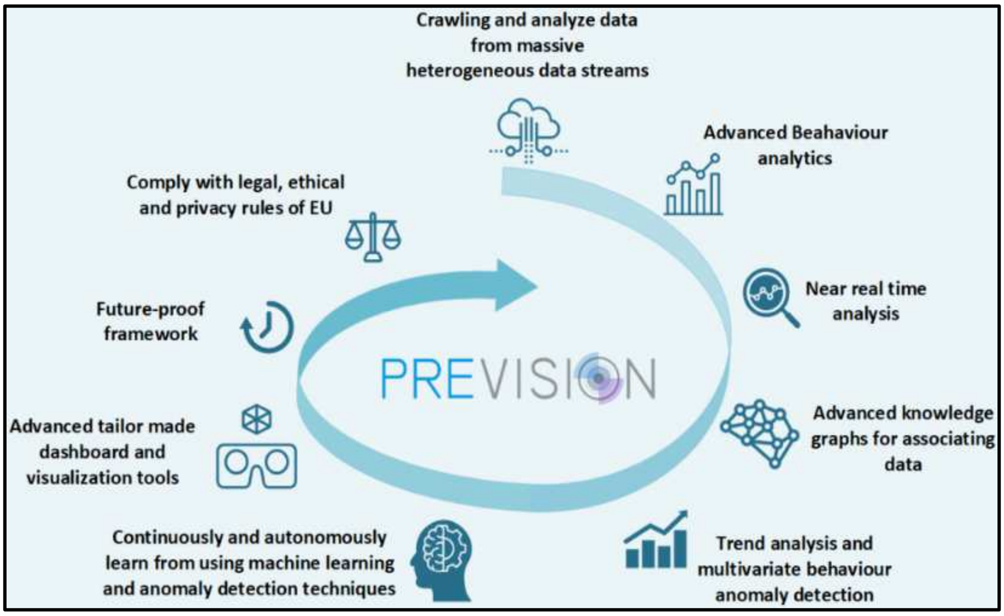


Figure 28. PREVISION conceptual framework [46].

The results of PREVISION project include:

i) a revised report on the characteristics of deviant behaviour, with a special focus on methods and models of predictive policing, for the detection of abnormal activities and predictive purposes. This contributes to combating cybercrime, organized crime and terrorism.

ii) the deployment of semantic technologies, providing a computable framework for systems to deal with knowledge in a formalized manner. The associated semantic information models were generated by machine learning algorithms allowing the discovery of correlations not initially foreseen whereas new information was extracted using reasoning processes.

iii) the adaptation of web HMI as the main element fostering applications integration and harnessing various solutions facilitating multi-dimensional data interaction, such as identification of radicalization and terrorist propaganda, protection of soft targets, fight against illicit trafficking and the analysis of cyber-criminal activities.

3.4.4.2.1 Relevance to OPTIMAI

In PREVISION, TRI is leading the WP on ethics and data protection and has prepared the project's data management plan. This experience will be used as reference within OPTIMAI for the Ethics and Policy activities of WP9. TRI will contribute to the Ethics and Policy activities as it will provide strategic, ethical, legal and regulatory advice on new technologies, and related privacy, data protection, ethical and societal concerns.

3.4.4.3 Factory2Fit

Factory2Fit stands for **"Empowering and Participatory Adaptation of Factory Automation to Fit for Workers"**. The concept of this project was human-centered and its goal was to combine the various skills of workers and motivate them for a total beneficial solution for industrial manufacturing enhancement. The core of this work was based on a dynamic user model that included physical and cognitive abilities. Considering workers as experts in their field made them more active and improved their performance. Furthermore, by combining their experience and skills with their performance feedback/award, workers were able to correct their own mistakes and always be active in learning and educated.

The Factory2Fit solutions have been developed based on extensive research into industrial needs, are highly relevant to manufacturing companies and address the biggest issues facing European factories today. These revolve around the following core issues; increasing worker empowerment, engaging the work community and improving the adaptability of both the worker and the workplace.

The Factrory2Fit project core diagram is depicted in Figure 29; It is considered as an employee-oriented system which contains the industrial experience of expert technicians and combines it with their feedback of their performance. it enhances production with adaptive solutions, and provide knowledge sharing. The main expecting results of this work is to enhance human-robotics cooperation, to increase work satisfaction, working conditions quality and productivity, as well as to reduce stressful working conditions and production faults [47].

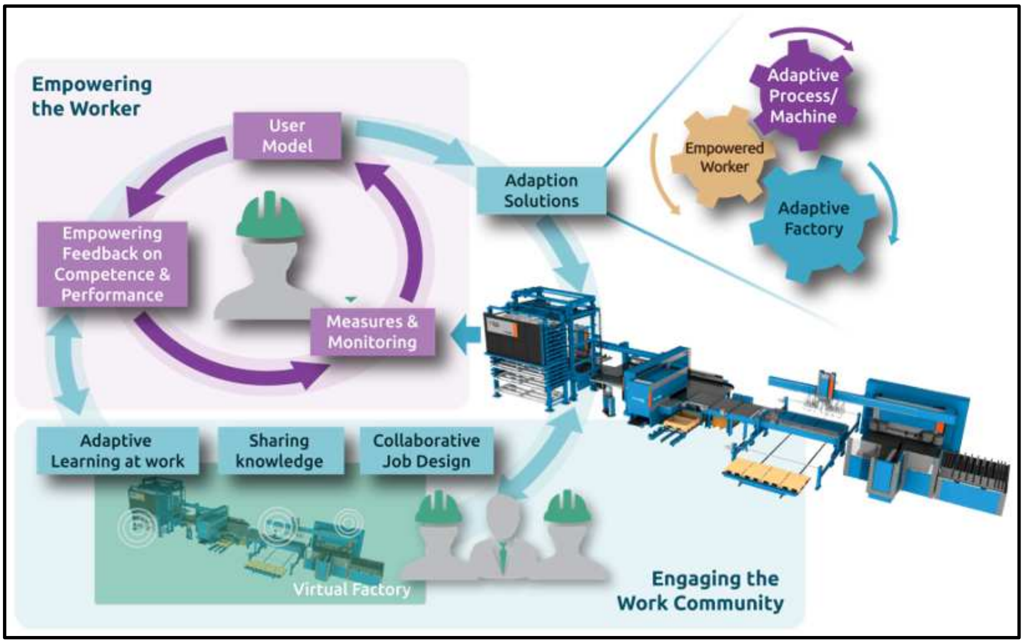


Figure 29. Factory2Fit project core diagram [48].

As regards the results of the project, the following Industrial innovations were developed: i) a worker feedback dashboard, that privately provides the worker with statistics concerning their well-being, productivity and work satisfaction over time, aiming at developing a culture of self-improvement. ii) a decision support system for dynamic task prioritisation and scheduling, that uses artificial intelligence (AI) to optimally assign tasks to both workers and industrial machines. The Decision Support System (DSS) is integrated with industrial machines so that it can instantly register any errors in machines and transfer work to others where necessary. This saves significant amounts of time and facilitates the distribution of tasks in sequential production processes. iii) a participatory design with virtual factory models, that allow workers to visualise new production lines or factories well in advance of construction, and ensure that all elements are ideally positioned. iv) a Social Media Platform for Contextual knowledge sharing and an Augmented Reality Guided Assembly that allow workers to instantly exchange information and knowledge and also share adaptive and dynamic live instructions with each other. v) Off-site and on-site Training Tools that allow workers to train in a model factory that replicates their work environment.

3.4.4.3.1 Relevance to OPTIMAI

CARR led the communications and dissemination activities and the collaboration with the Factory2Fit External Advisory Board and will transfer their experience in OPTIMAI.

Human operators are the key-asset in running a factory; providing them with easy-to-use tools and user-friendly working spaces enhances productivity. CERTH and VIS contributed to providing methodologies for maximizing the capabilities of the worker in the development of the factory of the future.

The results of Factory2Fit will be reused and extended in the OPTIMAI project. CERTH and VIS will bring their know-how utilized for resource allocation and predictive models. More specifically, virtual factory models and simulations employed as engaging platforms for the hands-on co-design of work practices, training and knowledge sharing could also be investigated in the OPTIMAI project. Finally, Augmented Reality (AR) based tools will provide sharing of knowledge and guidance in the OPTIMAI just as in the case of the Factory2Fit project.

3.4.4.4 KONFIDO

KONFIDO (2016: H2020-DS-SC1-2016 RIA) stands for "**Secure and Trusted Paradigm for Interoperable eHealth Services**". This work was focused on the healthcare domain, focusing on the eHealth concept. The vision of this project was to develop a cross-border e-health mechanism between countries. Such a model is very challenging, because it needs advanced digital security to protect personal data and privacy. This project was strongly connected with novel security extensions (Figure 30) including photonic technological security solutions (Photonic Physical Unclonable Functions, PUF), advanced cryptographic techniques (homomorphic), as well as the implementation of secure software (Security Information and Event Management, SIEM), transfer mechanisms (blockchain) and tailor-made e-IDs.

The conceptual architecture of this work is the following: Data are collected from individual's smartphones, and then transmitted along with various security levels for protection from cyber-attacks or any other unauthorized access. In the first layer, there is a blockchain mechanism, which records and stores individually the data for each ID. Furthermore, abnormalities are detected by a Security Information and Event Management system. Analytics are applied and correctional strategies are enforced to resolve any vulnerabilities during the processing and exchange of health data. The contributions of this project are exceptional, not only because it improves patients' healthcare regardless of their location, but also because of the guaranteed and secure way of e-health provision [49,50].

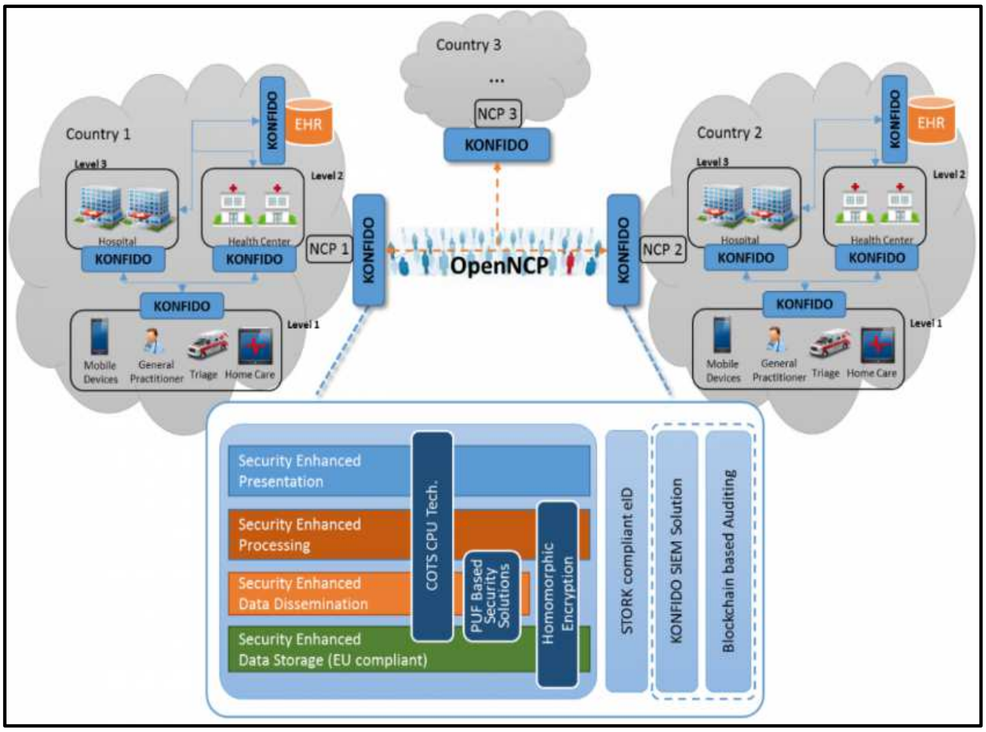


Figure 30. Architecture of KONFIDO [50].

3.4.4.4.1 Relevance to OPTIMAI

CERTH contributed to new methodologies to develop a scalable and holistic paradigm for secure inner- and cross-border exchange, storage and overall handling of healthcare data in a legal and ethical way. More specifically, knowhow and results on DLT technology and elements of the federated architecture of KONFIDO's solution will feed the design of the DLT layer in OPTIMAI. Effective logging and auditing mechanisms will be brought on to the project providing traceability and liability support within the OPTIMAI identity management infrastructure.

3.4.4.5 RECLAIM

RECLAIM (H2020-DT-FOF-06-2019) stands for "**Remanufacturing and Refurbishment Large Industrial Equipment**". The concept of this work was about remanufacturing and reinvestment of broken industrial mechanisms, to save industrial resources and faulty equipment instead of rejecting it.

This work was based on a decision support framework as illustrated in Figure 31. Its goal was lifetime expansion, productivity enhancement and diagnostic maintenance of the electromechanical industrial equipment by using state-of-the-art technologies like IoT sensors, advanced prediction and process optimization techniques, fog computing, and augmented reality. There are demonstration cases in several countries, such as:

- Lifetime extension of friction welding machines (Germany)

- Maintenance and upgrade of machines in the shoemaking industry (Spain)
- Maintenance, refurbishment and upgrading of a bleaching machine (Turkey)
- Predictive maintenance and refurbishment of a large woodworking production line (Switzerland)
- Modernization and refurbishment of a white enameling line (Chez Republic)
- Refurbishment and renovation of robot cells for making tubs (Switzerland)

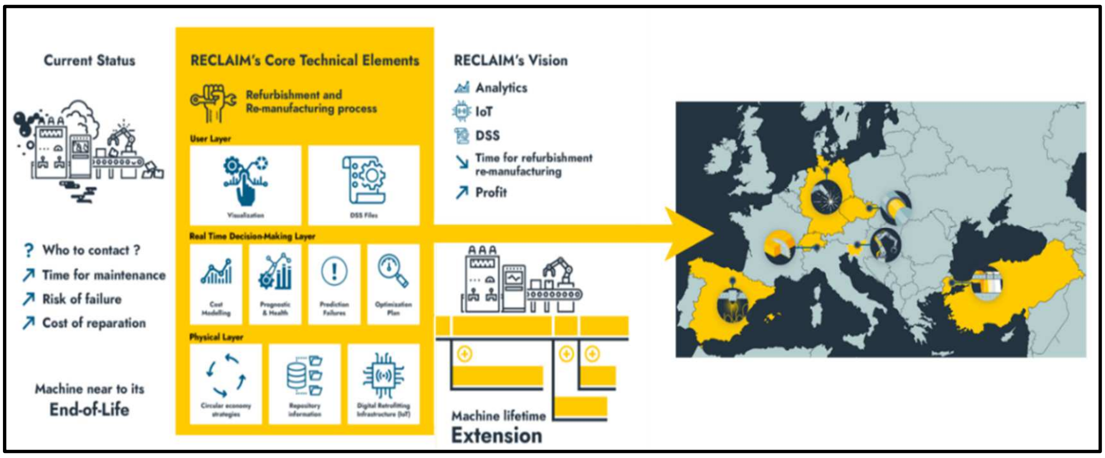


Figure 31. RECLAIM's conceptual framework [51].

The innovation of this project is the development of a novel Decision Support Framework that guides the optimal refurbishment and re-manufacturing of electromechanical machines and robotics systems. The framework uses IoT sensors, novel prediction techniques using advanced ML models, and process optimization techniques to offer machine lifetime extension and thus increased productivity.

A result of this work is the enhancement of industrial efficiency, as well as its financial strengthening. Its implementation in companies will enhance manufacturing and EU economy [51].

3.4.4.5.1 Relevance to OPTIMAI

During the RECLAIM project, CERTH contributed to the technological core of the project and mainly to the design and development of real-time optimization tools, ensuring optimized multiple criteria DSS-based maintenance scheduling. Furthermore, CERTH led all aspects concerning the Decision Support System and developed several algorithms (data-driven, model-based, and knowledge-based) that are applicable for the detection, isolation and forecast of the faults, at component and machine level. Finally, CERTH also undertook the development of cybersecurity by design embedded solution. FINT is also partner of RECLAIM project and is focusing on the development of the IoT modules which will be used in the manufacturing environments for the equipment upgrade (IoT smart GW enabling Edge computing with heterogeneous processing). FINT is also developing and providing Machine Vision Systems to 3 out of 5 pilots. Moreover FINT is contributing to the holistic IoT platform enhancement and cloud/edge orchestrated smart equipment modules development, enabling re-manufacturing and refurbishment with predictive maintenance capabilities. This experience of both partners will be used as reference within the OPTIMAI project concerning the development of an innovative and state-of-the-art IoT Platoform and Decision Support System for early notification regarding defects during the manufacturing process.

3.4.5 Summary of EU-funded projects relevant to OPTIMAI

The most common and well-known methodologies in Industry 4.0 and Smart Manufacturing include Digital Twins, Fault Detection, Smart Metrology, Augmented Reality, Quality Control, Computer Vision, Predictive Maintenance, Zero-Defect Manufacturing and Internet of Things. These technologies were investigated and implemented in the related projects presented in this section. Each EU-funded project has deployed two or more of the aforementioned technologies, to provide solutions to certain tasks, according to their objectives, results and forthcoming advancements. Figure 32 and Figure 33 graphically represent the spread/distribution/presence of each technology into the examined projects. It is worth mentioning that FORTISSIMO2 integrates the full list of these state-of-the-art technologies into the implementation realization of its engineering and manufacturing framework.

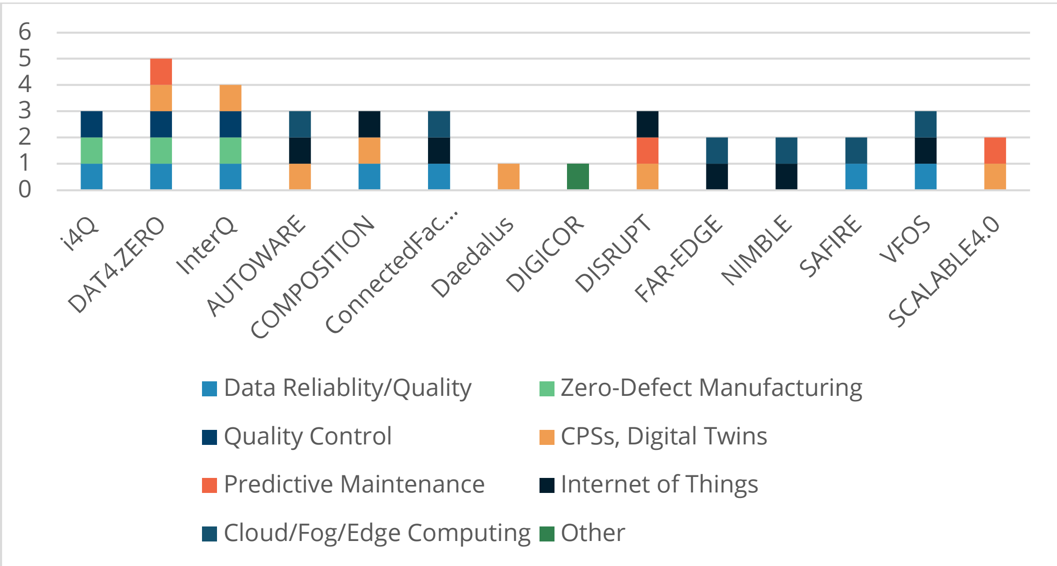


Figure 32. Technologies employed in each FoF-11 EU-funded project.

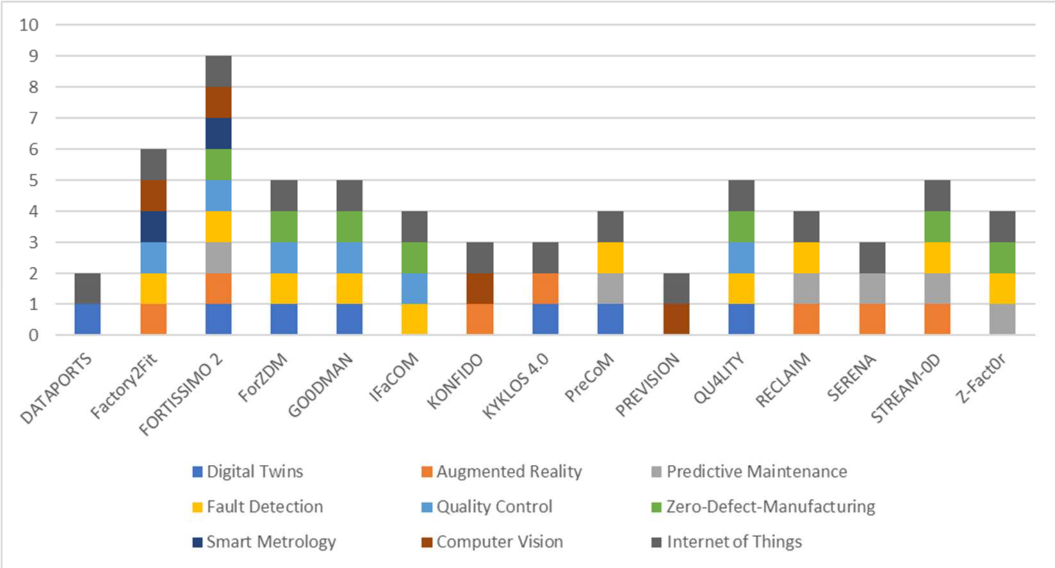


Figure 33. Technologies employed in each EU-funded project.

3.5 Results and Findings in Literature

In this section, we present the main findings in literature regarding smart manufacturing domains where AI technologies have found great applicability. Due to the demand for advanced analytics to transform unprecedented volumes of data into actionable and insightful information for smart manufacturing, ML and mainly the breakthrough in AI deep learning received a lot of attention as the leading innovation in computational intelligence.

Machine Learning (ML) is the ability of smart systems to learn and improve through experience gained from historical data, without the need of programming, or any other human intervention [52]. Various types of ML are available, such as Supervised, Unsupervised, Semi-supervised and Reinforcement Learning. Commonly used ML techniques are Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs). Some quite accurate and generally acceptable descriptions for these technologies are provided in [3,53].

Common ML methods are reviewed in [54] for intelligent manufacturing, and an extensive discussion on their strengths and weaknesses in a wide range of manufacturing applications is provided. In a recent comparative review study *on machine learning algorithms for smart manufacturing*, various well-known ML techniques, including Artificial Neural Network, Support Vector Machine, and Random Forest, were implemented for machining tool wear prediction [55]. Also, ML techniques including neural networks, fuzzy logic, genetic algorithms, and hybrid systems were reviewed for the decision making and monitoring of machining operations [56]. Traditional machine learning is usually designed with shallow structures, such as Artificial Neural Network, Support Vector Machine, and logistic regression, etc. By coping with limited handcrafted features, it achieves decent performance in a variety of applications. However, the massive data in smart manufacturing imposes a variety of challenges [57], such as the proliferation of multimodal data, high dimensionality of feature space, and multicollinearity among data measurements. These challenges render ML algorithms struggling and thus greatly impede their performance.

Deep Learning (DL) is an extension of ML and describes the ability of smart systems to imitate human brain functionality in tasks such as decision making and data processing. In smart manufacturing, DL has found significant applicability for processing and analysing big manufacturing data. The most popular DL methods are the following:

a) Deep Neural Networks (DNNs). A DNN is resembled by an ANN with many hidden layers. The difference is in the training process. DNN uses deep learning as a class of machine learning algorithms with the following main aspects: (a) use a cascade of multiple layers of nonlinear processing units for feature extraction and transformation, (b) learn in supervised (e.g., classification) and/or unsupervised (e.g., pattern analysis) manners, and (c) learn multiple levels of representations that correspond to different levels of abstraction; the levels form a hierarchy of concepts. DNNs have more than three layers, trained to model non-linear problems.

b) Convolutional Neural Networks (CNNs). They are among the most powerful deep learning techniques presenting notable capabilities on analyzing and classifying images. They are mainly employed in image processing applications (semantic segmentation, image classification, instance segmentation, object detection, etc.). Their neurons architecture is based on the features of images they process (width, height, depth, etc.). Typical CNNs have a similar structure with ANN and consist of one or more filters (i.e., convolutional layers), followed by aggregation/pooling layers in order to extract features for classification tasks. Since a CNN has similar characteristics with a standard Artificial Neural Network (ANN), it uses gradient descent and backpropagation for training tasks, whereas it contains additionally pooling layers along with layers of convolutions. The vector that is sited at the end of the network architecture can deliver the final outputs.

c) Residual Neural Networks (Res-Nets). They are an extension of DNNs. They are highly considered in industrial applications where precision is vital for machinery health-state diagnosis. Res-Nets typically perform better than CNN-based approaches.

d) RNN: Recurrent neural networks (RNN) are artificial neural networks (ANN) that utilize connections between units in order to form a directed graph along a sequence. RNNs use their internal memory to process such sequences, something that is not met in feed-forward ANNs. However, RNNs suffer from short-term memory from the problem of vanishing gradient during back-propagation. This is solved by the Long Short-Term Memory (LSTM) algorithm.

e) LSTM: LSTM excels over the original RNN due to the specific cell structure it has, which gives the algorithm the ability to add or remove information from this cell by structures that are called gates. These gates control this memorizing process by allowing the model to learn which information to store in the long memory and which to discard. The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation. LSTM has been applied in predictive maintenance and prognostics in manufacturing processes.

DL techniques enable people to (1) automatically learn from data, (2) detect underlying patterns, and eventually (3) make efficient decisions. With automatic feature learning and high-volume modelling capabilities, deep learning provides an advanced analytics tool for smart manufacturing in the big data era. It uses a cascade of layers of nonlinear processing to learn the representations of data corresponding to different levels of abstraction. The hidden patterns underneath each other are then identified and predicted through end-to-end optimization. Thus, DL offers great potential to boost data-driven manufacturing applications [58]. There are several review papers extracted from the related literature, which show the actual implementations of ML and DL methods in factory operations within the smart manufacturing domain.

The authors in [59] performed a review study focused on Applications and Challenges of Machine Learning Techniques in the domain of Smart Manufacturing. This study provides an overview regarding several ML algorithms (e.g. support vector machine, k-nearest neighbor, neural network etc.) which bring notable improvements inside different manufacturing areas, such as optimization, quality control, prediction of failure, cost reduction and transparency. Future trends of ML applications for smart manufacturing are also discussed.

Additionally, a systematic review of recent ML application for manufacturing processes was presented in [60]. This review study focused on the efficient application of various DL models including Convolutional NN and other Deep NN architectures, in certain Smart Industry processes such as image recognition and object detection, thereby enhancing industrial solutions.

In another review study [58], a comprehensive overview of deep learning techniques is presented with the applications to smart manufacturing. In particular, deep learning methods are discussed concerning their applications in Smart manufacturing for improving system performance and decision-making, as well as for optimizing production systems. Typical Deep Learning models such as Recurrent NNs, LSTM and Deep CNNS play a key role in automatically learning from data producing different levels of data analytics, such as diagnostic and predictive, mainly used for fault assessment and defect prognosis of Manufacturing systems. A comparison between different deep learning models, CNNs, RNNs, LSTM and Auto Encoder, highlighting their pros and cons in the areas of product quality inspection, fault diagnosis, and defect prognosis.

Figure 34 depicts an overview of deep learning enabled advanced analytics for smart manufacturing, highlighting the different levels of data analytics, including descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. With the advanced analytics provided by deep learning, there are many benefits which include reducing operating costs, keeping up with changing consumer demand, improving productivity and reducing downtime, gaining better visibility and extracting more value from the operations for globallcompetitiveness. It is noted that DL plays a key role in many aspects of the smart manufacturing domain.

However, there is no previous review study or paper to discuss the ML and DL applications towards the domains investigated in this deliverable, including Artificial Intelligence for Industry, Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision, Augmented Reality and Zero-defect manufacturing.

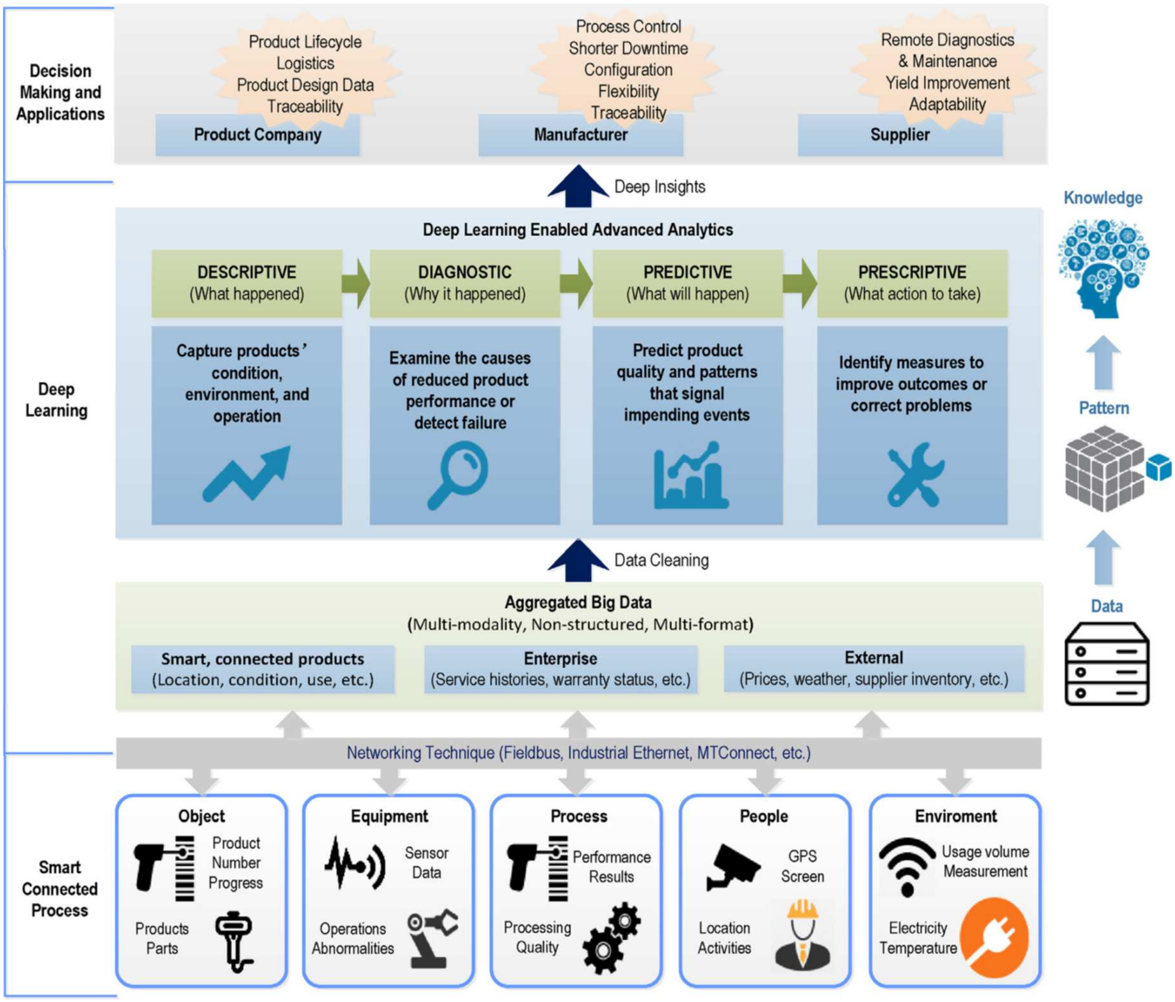


Figure 34. Deep learning enabled advanced analytics for smart manufacturing.

In what follows, we present the articles found in the related literature which encapsulate the AI technologies in each one of the above fields of smart industry. The reviewed articles are listed below, in chronological order (yearly) from oldest to newest for the respective period (Jan. 2015 to April 2021).

3.5.1 AI for industry

3.5.1.1 2016

Klancik et al. proposed in [61] an automatic programming approach of CNC machine tools using artificial intelligence methods. The methodology takes into consideration the digital CAD model of the part and the introduced system automatically creates a CNC program which can lead to accurate and efficient results during material removal processes. The suggested system utilizes NSGA-II multi-objective optimization and swarm intelligence. More specifically, the prediction module proposes suitable values on the machining parameters, as well as the appropriate tools and tool paths of the machining process. The suggested methodology was experimentally validated in a use case of a machining process and the results showed that with the aid of Artificial Intelligence the material removal operations could eventually be automatically programmed.

Lover et al. [62] presented a study where several machine learning algorithms were examined in order to evaluate the most efficient one to predict the manufacturing cost of jet engine components. The results of the work revealed that GBT (Gradient Boosted Trees) and SVR performed better compared to Neural Networks and Multiple Linear Regression. The work proved that machine learning technology could be an affordable and efficient technique to estimate the cost of manufacturing parts during the early stage of the design process in an industry.

3.5.1.2 2017

Pou and Leblond discuss the outlooks of smart metrology systems [63]. Smart metrology is a candidate to replace the good old "worst-case scenarios". Continuous monitoring can assess the status of the production process and eliminated unnecessary calibrations. Furthermore, methods of artificial intelligence can process the "Big Data" produced by the distributed sensors.

3.5.1.3 2019

Wang et al. proposed productions planning for additive manufacturing applications using a computer vision-based approach [64]. The proposed approach was to (1) sort tasks based on their heights, areas and remaining time to deadline, (2) project models on the printing plane, and (3) apply a vision-based method to find high quality packing solutions. According to the authors, despite the high efficiency of the method, there is still much space for improvements, e.g., fine-tuning of hyperparameters, upscaling to larger scenarios etc.

3.5.2 AI for metrology

Metrology in industry can be described as measurements methods that are used to quantify the quality of a product in order to examine if the produced part meets the requirements of the production. Depending on the applied manufacturing process and the application, certain physical parameters of the product need to be measured and compared to reference values or models. The main concept is the employment of several types of sensors within the process to measure some indicative variables in order to determine the quality of the product. In the past years, machine learning methods have been applied in measurement methodologies to achieve high standards during the production stage. One of the main reasons that machine learning technology is considered an appropriate approach in metrology science is based on the ability of machine learning algorithms to extract data and develop models from an existing database. These methods have been utilized in several contexts as documented in the next paragraphs.

3.5.2.1 2015

Rana et al. [65] present a predictive data analytics and ML enabling metrology and process control for advanced integrated circuits (IC) fabrication. It is about the precise prediction of IC characteristics through electrical testing of the produced components. Predictive metrology combined with ML is used to investigate two cases, by using a scatterometry equipment, for the early prediction of deep trench capacitance modeling and the metal line resistance modeling.

In the deep trench capacitance have been used Multivariate Linear Regression models, as well as NN. As an overview, NN seems to be more accurate in predictions. Although, for the deep trench capacitance, a Partial Least Square model and a NN have been developed. As compared, the PLS performance tends to provide a better correlation to the real measurements.

In the same sense in [66], Rana et al. have examined the physical critical dimensional of 18 nm half pitch pattern in EUV resist. For that purpose, have been implemented NN models and Multivariate Linear Regression models. Undoubtedly, NN seem to provide more efficient results in physical critical dimensional forecasting than MLR approach.

Du et al. [67] propose a selective multiclass SVM classifier for surface classification using high-definition metrology. This approach is implemented with a dual-tree complex wavelet transform, in order to analyze 3D surface and then a SVM-based classifier is used for classification of surface's mined data. As it has been testified in real industrial data, the proposed two stage architecture effectively classifies clear engineering surfaces.

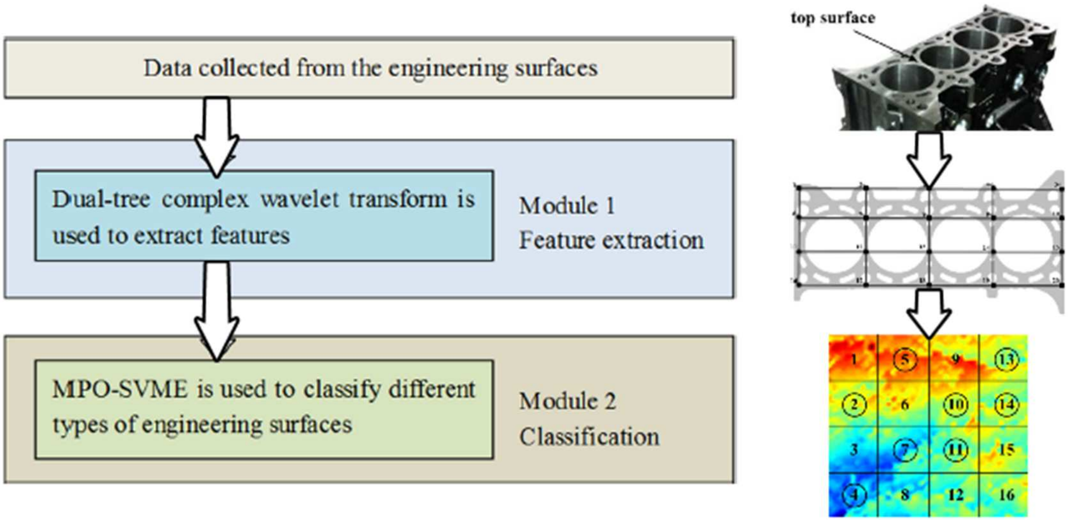


Figure 35. Selective multiclass SVM classifier architecture[67].

Similarly in another study, Du et al. [68] have developed an adaptive SVM-based classification system for various workpiece surfaces using high-definition metrology. The proposed framework of classification system is depicted in the following figure. A Non-Subsampled Contourlet Transform is combined with a SVM classifier. More precisely the SVM classifier is based on Adaptive Particle Swam Optimization algorithm and a Varied Step-Length Pattern Search algorithm.

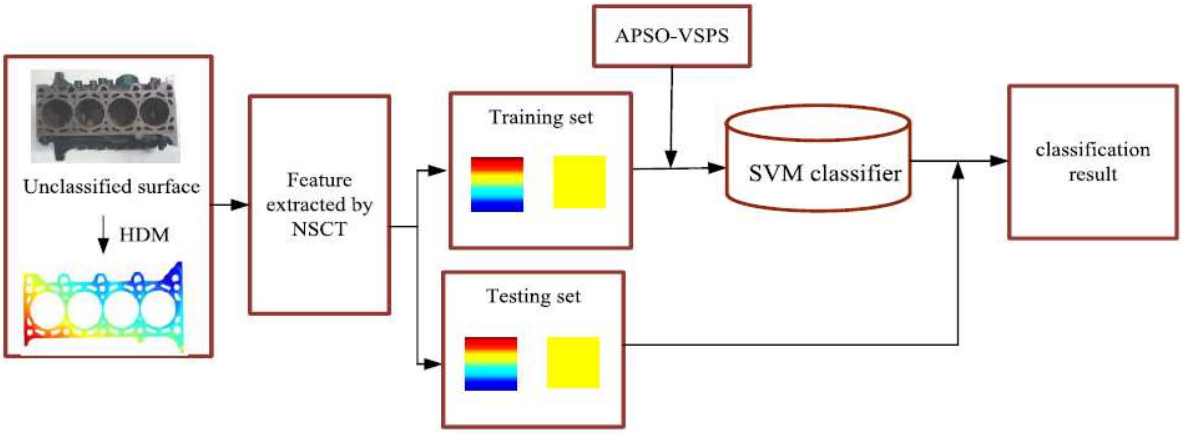


Figure 36. Classification framework [68].

It is claimed that this algorithmic-based approach can classify workplace surfaces in a high efficiency. This framework can be implemented in process monitoring, fault diagnosis and machine-tools condition forecasting, although the classifier has to be regulated each time a different surface is tested.

Koblar and Gantar [69] have been occupied with surface's roughness determination of semi-finished products applying a combination of computer vision and ML. For this purpose, have been implemented classification techniques, in order to separate the acceptable roughness values, and regression models to estimate surface's roughness level of every produced item.

3.5.2.2 2016

Kuo and Faricha [70] present an ANN approach for diffraction-based overlay measurement. In this research is investigated the precision improvement of forecasting in sidewall angles. For this purpose, they have been tested a feed-forward ANN model, a conventional linear model and a regression model. As an efficiency comparison result, it is claimed that ANN perform more accurate in offset shifting forecasting than both other models, reducing in that way inhomogeneous intensity deviations. The outcome of this survey is that optical scatterometry can be combined with ANN approach implementing a wider wavelength optical beans exposure, in order to estimate the overlay percentage.

Kang et al. [71] have developed a semi-supervised application of VM based on semiconductor manufacturing. For this purpose, is used a Support Vector Regression model based on self-training. This system is trained to handle the uncertainty of unnamed data and estimate them by applying Probabilistic Local Reconstruction models. The experimental outcomes of this application point can enhance in the efficiency of results by 8%, as well a reduction of 20% on training process of the system, in comparison with the classical SVR approach.

3.5.2.3 2017

In order to apply smart metrology into a workpiece there are some parameters that need to be specified [72]. The geometrical and functional characteristics of the object, as well as the need that serves this object are these features that have to be cleared. Implementing advanced smart metrology, a product life cycle could consist of the following stages, products designing, manufacturing stage and verification process of the total product. Product quality can be enhanced by enabling automation smart metrology-based systems. The basic sectors of such a system includes the sensorial layer, the layer of material handling, the production layer and the monitoring layer. It is clear that this system can be a steppingstone in Integrated Management Systems based on Advanced Process Control.

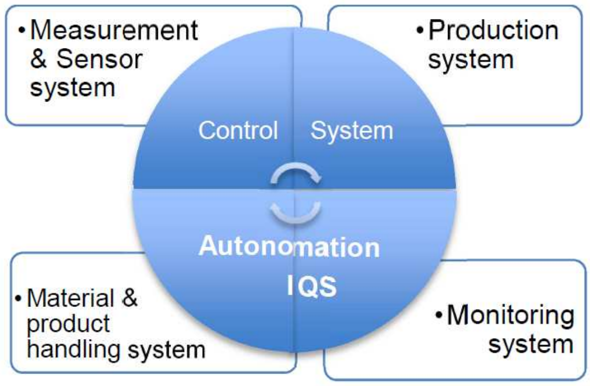


Figure 37. Autonomous quality assurance system [72].

Terzi et al. [73] propose a virtual metrology modelling approach with optical emission spectroscopy data, able to replace the manually data mining way. As it has been tested on a real semiconductor manufacturing case, it is claimed that for this purpose CNN can surpass the Ridge Regression algorithm.

Vakharia et al. [74] developed a feature extraction and classification approach of machined component texture images, by combining AI approaches combined with Wavelet transform. For the image texture identification have been used ANN and SVM methods, resulting in a highly precise identification performance between 87,5% and 100%. As it has been tested, it is claimed that ANN show a greater result than SVM in texture characterization.

Shao et al. [75] present a support vector regression approach for highly precise prediction purposes of a 3D machined surface, via topography. For this task, is proposed a spatial-temporal based multioutput support vector regression model. As it has been testified in engines' cylinder block surface it is resulted that such an approach is able to predict surface's topography, although the prediction process needs numerous times to be tested, as it is prone to misleading results.

Kagalwala et al. [76] made a research focused on measuring characteristics on slightly thick (i.e. 7nm nodes thickness) 3D surfaces in Semiconductor manufacturing, aiming at a highly accurate and efficient way. It is claimed that by exploiting properly numerous information canals, can be achieved precise measurements, independently the sensitivity difficulties and measurement's quality. In the same sense is implemented a combination of Optical Critical Dimension metrology and ML. It has been concluded that, hybrid metrology combined with VM can enhance accuracy, although, measurements stability is under research.

Susto et al. [77] investigate anomaly detection approaches in semiconductor manufacturing. Precisely speaking, this is a ML comparison research, between methods such as Principal

Component Analysis, Angle-based Outlier Detection, Local Outlier Factor, aiming to locate any inhomogeneities on the industrial data, of the etching process. It is claimed that the Local Outlier Factor approach seems to provide the most accurate result.

Kholief et al. [78] propose a contactless novel ML approach for fault detection of steel surfaces. For that purpose, are implemented two types of classification techniques, a feed-forward ANN and a Deep Autoencoder Network. These classifiers are trained from flawed captured surface's frames to classify steel defects (i.e., scratches, patches etc.). This system's results are based on a 1800 grayscale analysis verification and it is claimed that it has achieved an approximate zero error in fault detection, showing an efficient result. The effectiveness of the proposed DAN and ANN is verified using 1800-grayscale images for six popular classes of steel defects that prepared by NEU as crazing (Cr), patches (Pa), pitted surface (PS), inclusion (In), rolled-in scale (RS) and scratches (Sc).

3.5.2.4 2018

Zhou et al. employed convolutional neural networks in Fourier-transform profilometry [79]. The image recognition and feature extraction capabilities of CNNs were exploited to enhance the method. Specifically, CNNs were employed to analyze the spectrum image in order to identify carrier frequency components associated with the details of the inspected object.

Senin et al. [80] discussed the outlooks on measurement enhancement using disruptive technologies of artificial intelligence, explaining that AI can be used to take advantage of the a priori data, the measured object (even past measurements) and, in combination with a functional measurement model, accelerate the measurement procedure and make it more efficient. An example of IRM (Information-rich metrology) which leverages AI to perform the measurements can be found in the microelectronics industry, where scatterometry data is used to accurately predict track resistance and, therefore, preempt failures in integrated circuits.

Delli and Chang [81] developed an in situ procedure for quality control in Additive Manufacturing procedures using the Support Vector Machine algorithm, image processing and a camera. Several stages of the process were captured and according to the geometrical characteristics of the printed part, a SVM model classified the procedure as 'defective' or 'good'. With the aid of this technique, defect detection during the manufacturing procedure is feasible and could lead in eliminating waste of production time and feedstock material. Experiments in laboratory using PLA and ABS as feedstock materials demonstrated the effectiveness of the method.

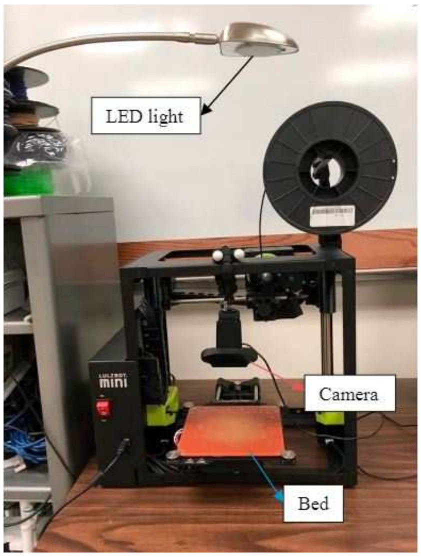


Figure 38. Hardware setup [81].

In general, the quality of a machined surface can be evaluated via its surface finish, which is a parameter that is deteriorated if the tool's wear is increased. Therefore, the measurement and the prediction of the surface roughness on a manufactured part is essential. In Pimenov et al. [82], several AI models were applied, such as random forest, standard Multilayer perceptrons (MLP), Regression Trees, and radial-based functions to provide information to the production line during the process about the expected surface roughness of the manufactured product. In addition, the parameters' tuning of the employed models was accomplished via the grid search and the proposed methodology was tested on face-milling of a structural steel 45.

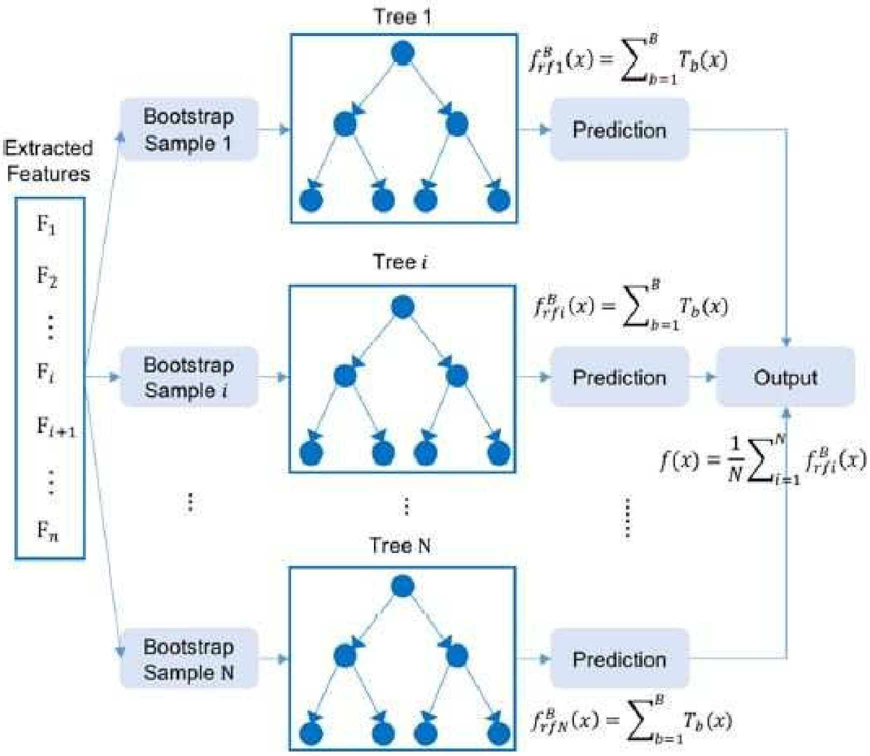


Figure 39. Tool wear prediction utilizing RF models [82].

Khang et al. [83] have studied a NN virtual metrology approach able to surpass the lack of data, based on transfer learning. In this work transfer learning is implemented in order to train new equipment's VM models, by transmitting knowledge from already trained old equipment's VM models. It is showed that NN are suitable for accurate and efficient predictions, independently of datasets unavailability and knowledge resources are reduced.

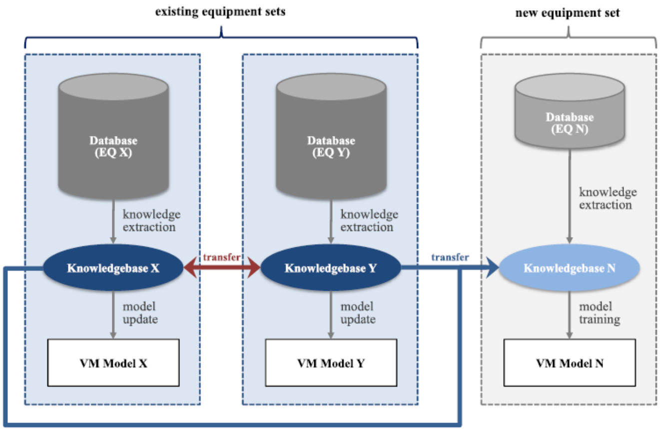
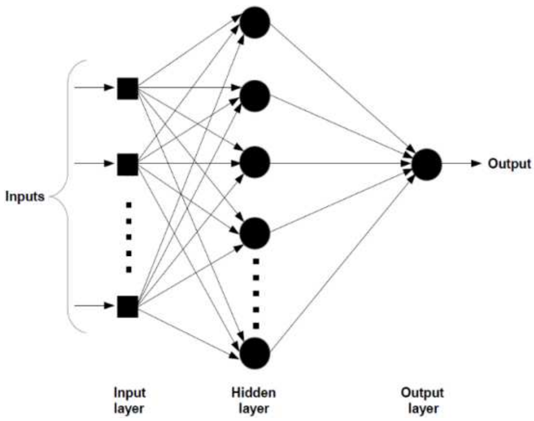
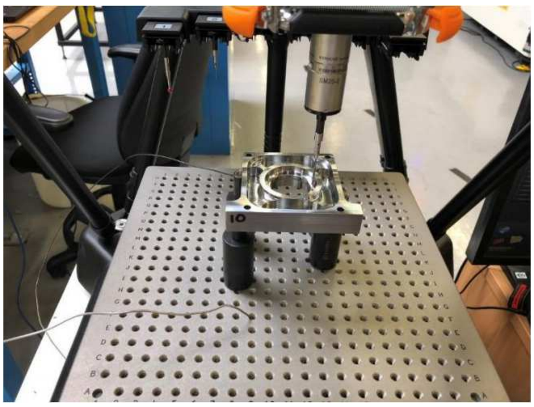


Figure 40. Application of transfer learning to virtual metrology with multiple equipment sets[83].

3.5.2.5 2019

Papananias et al. [84] developed an intelligent metrology informatics system based on neural networks for multistage manufacturing processes. The goal was to assess the quality of a product after the manufacturing process, which included heat treatment and machining. They employed a MLP network with eight inputs, one hidden layer with 10 neurons and one output. The inputs were associated with measurable properties, such as RMS values from inspection sensors, surface hardness of the material, etc. The predicted results were validated against experimental measurement and were found in good agreement. The presented model lacks the capability to quantify prediction uncertainties, thus, further development and improvement is possible.





(a) (b)

Figure 41. Intelligent metrology informatics system based on neural networks for multistage manufacturing processes [84]. (a) Architecture of the employed MLP. (b) Comparative coordinate measurement.

Hou et al. [85] prepared a paper of a research related to AI on edge device for laser chip defect detection. Machine learning has been a major driver for improving semiconductor laser chip manufacture process. The virtual metrology system was used to enable the manufacturers to conjecture the wafer quality and deduce the causes of defects without performing physical metrology. However, building the virtual metrology system required a large amount of classified chip images. Therefore, a fast, accurate, portable image classifier was needed to fit modern flexible semiconductor laser manufacture setup, even without Internet connection, based on a few pre-trained deep learning modes (AlexNet, ZFNet, and GoogLeNet) in this case.

Wasmer et al. [86] propose a ML approach based on additive manufacturing using acoustic emission. Acoustic emission is used to collect data of surface and Reinforcement Learning technique is used to clarify the meaning of collected data. Combining both these methods is aimed to be accomplished an in-situ quality supervision. The developed approach seems to provide efficient real-time quality classification results, reaching a level of accuracy 74-82%.

3.5.2.6 2020

Lee and Kim [87] used convolutional neural networks for virtual metrology during semiconductor manufacturing. The proposed model combined a recurrent neural network and a convolutional neural network to extract time-dependent and time-independent features. The model performance was compared to its best-known competitor (elastic-nets) and it was found that a 8.48% decrease in process variability was achieved.

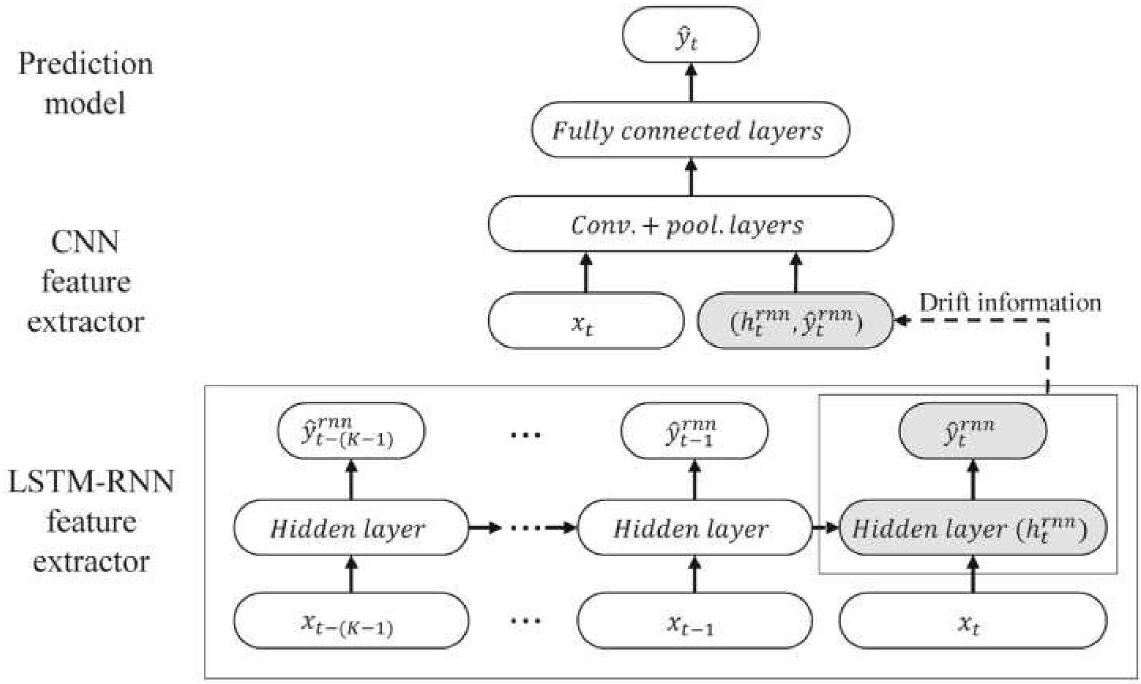


Figure 42. Architecture of the proposed model [87].

Rendon-Barazza et al. proposed the incorporation of artificial intelligence into optical metrology systems [88]. They employed deep learning analysis in optical microscopy and achieved measurements of accuracy around 0.77nm, which is comparable to the accuracy of electron beam and ion beam methods.

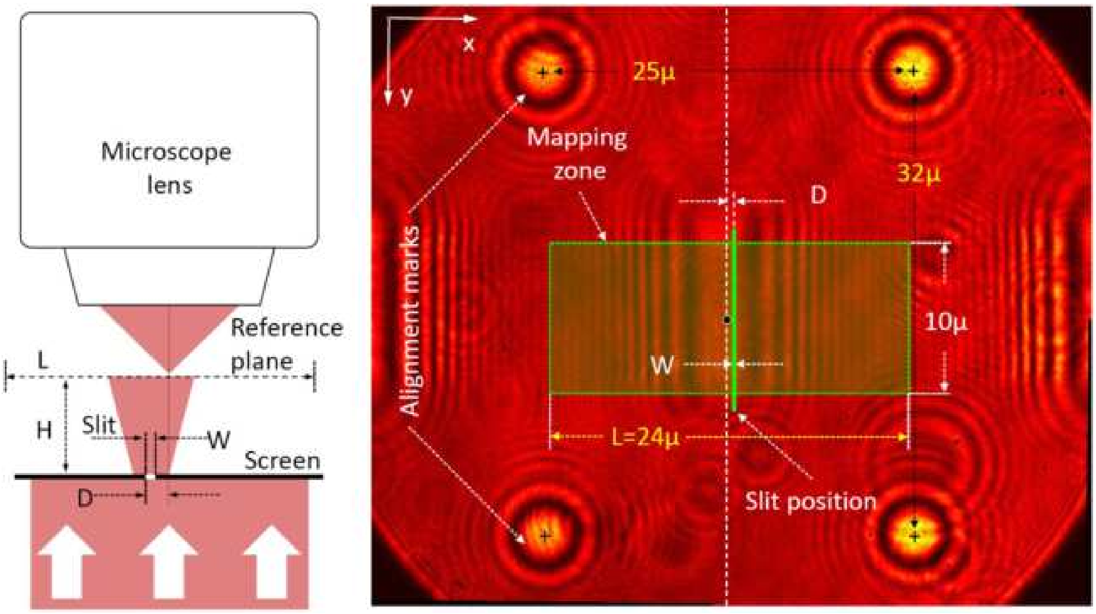


Figure 43. Measurement of sub-wavelength objects using AI-enhanced optical microscopy [88]. Left: Conceptual representation of the setup. Right: Recorded intensity field.

Kotsiopoulos et al. [89] developed a quality assurance system that is applicable in machining operations. The suggested technique automates the 3D inspection and the monitoring process of defective metal components via the employment of Deep Neural Networks. The necessary data were extracted from real production processes utilizing shop-floor sensors, an ultrasound scanner as well as a laser micro-profilometer. The production monitoring module analyzes data from the employed sensors for quality control tasks and suggests a fusion scheme in order to enhance even more the accuracy of the manufacturing procedure.

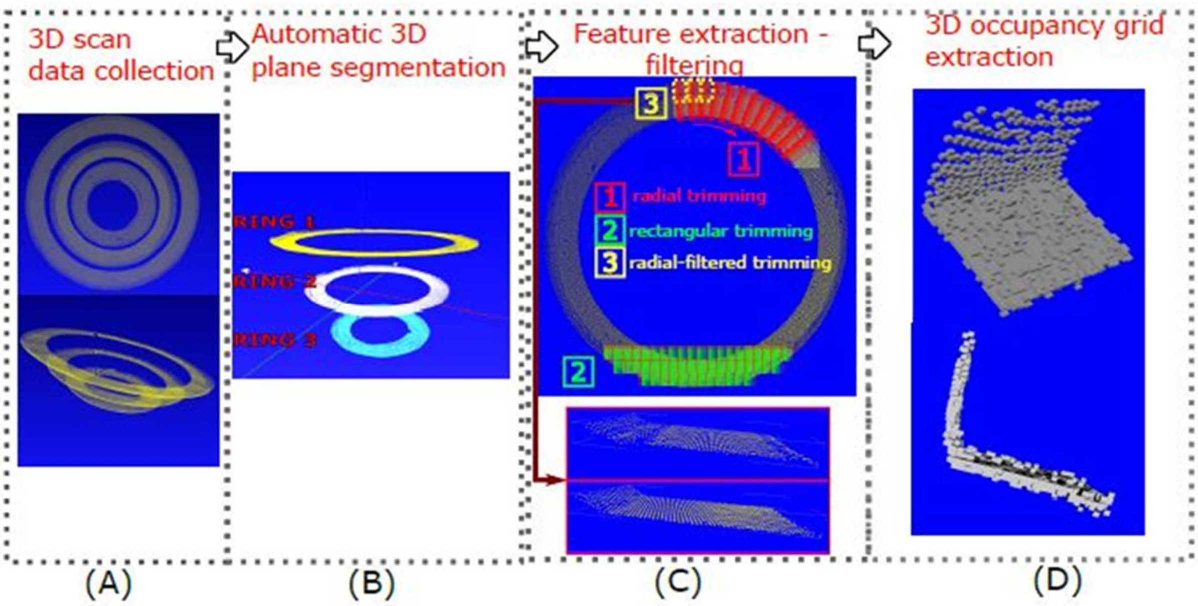


Figure 44. Pre-training data for the 3D laser scanning tool [89].

3.5.2.7 2021

Charalampous et al. [90] presented a method that employed various regression-based machine learning algorithms to estimate the dimensional deviations between an additively manufactured product and its corresponding nominal digital 3D model. The introduced methodology was validated in real-life manufacturing parts with complex geometrical characteristics. Furthermore, a compensation technique was applied to adjust the dimensions of the digital 3D model in order to compensate the overall dimensional deviations of the printed object increasing that way the performance of the AM process.

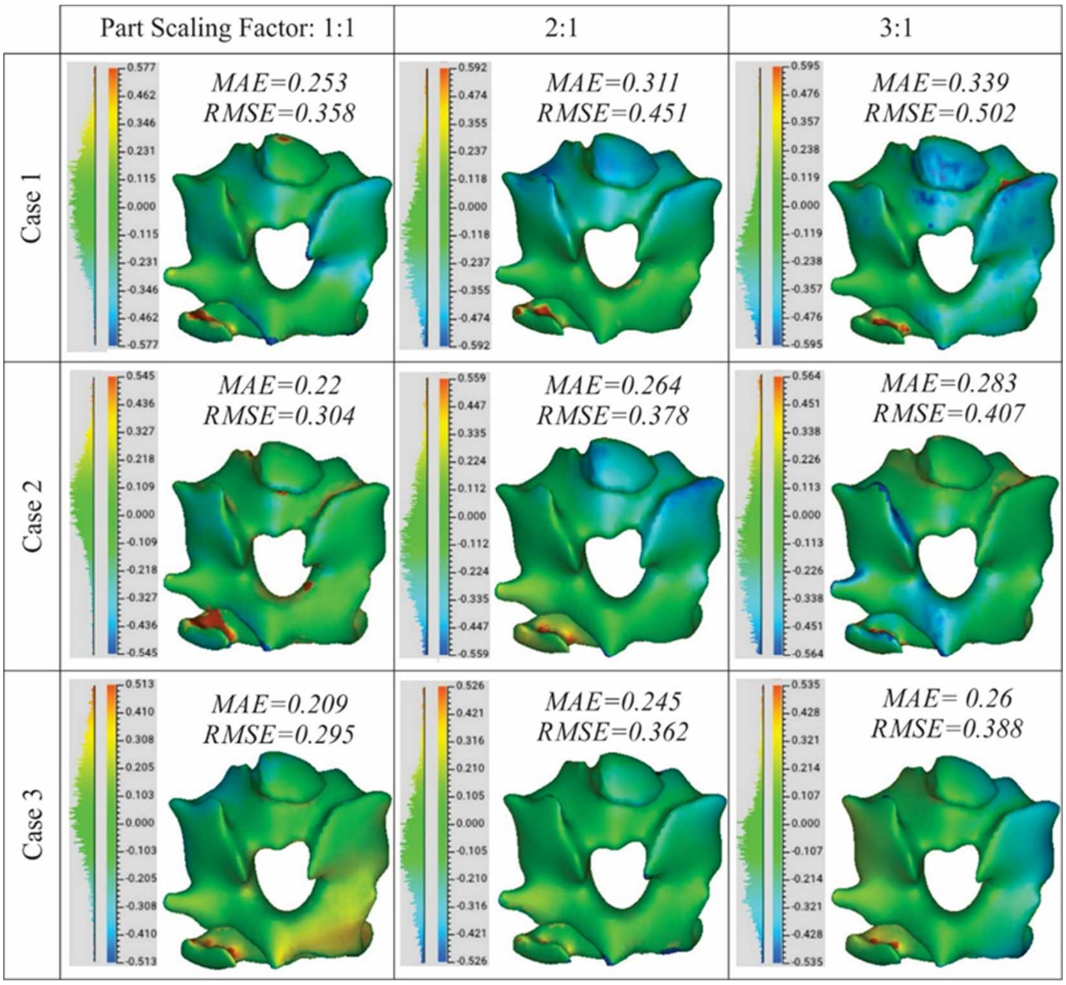


Figure 45. Surface Distance Maps on a freeform object [90].

3.5.3 AI-enhanced digital twins

The main purpose of digital twins is production visualization, along with all its possible extensions and benefits, such as: comparisons between expected and actual behavior, virtual trial-and-error to identify best practices etc. Preliminary information in the area of the digitalization of the manufacturing industry can be found online [91]. This is further supported by research employing digital twins in the classic form, i.e. without AI integration. Zhang et al. [92] propose a product manufacturing digital twin (PMDT) model which consists of a five model pipeline and a new architecture of cyber-physical production system (CPPS) that focuses on the production phase in smart shop-floor. Lu and Xu [93] propose a path towards resource visualization for developing cyber-physical production systems. However, most important for OPTIMAI is the incorporation of AI algorithms and techniques in digital twins, as described in following paragraphs.

3.5.3.1 2017

Vachálek et al. [94] suggested the use of digital twins on production lines. The physical production line works in parallel with a virtual one. Communication between the virtual and the physical system leads to optimized operational conditions by the use of genetic algorithms.

3.5.3.2 2018

Jaensch et al. [95] propose a combined model-based and data-driven concept of a digital twin. They show how to use machine learning in connection with suitable models, in order to archive faster development times of manufacturing systems.

3.5.3.3 2019

Wang et al. [96] presented a digital twin for fault diagnosis in rotating machinery. The digital twin acted as the reference structure for the physical system, which enabled the connection and provision of data and information in a unified model. The digital twin system could be used for fine-tuning the system (Figure 46) as well as fault diagnosis (Figure 47). The data collected during operation of the rotating system is fed into the digital twin, and it is processed to assess fault status. The system is quite promising as the assessment error is limited to around 5%.

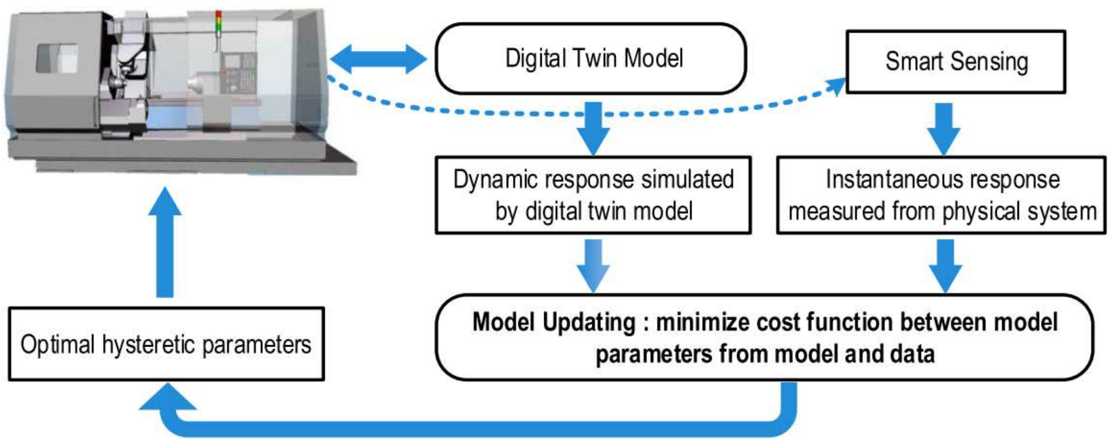


Figure 46. Digital twin mapping scheme by model updating; courtesy of [96].

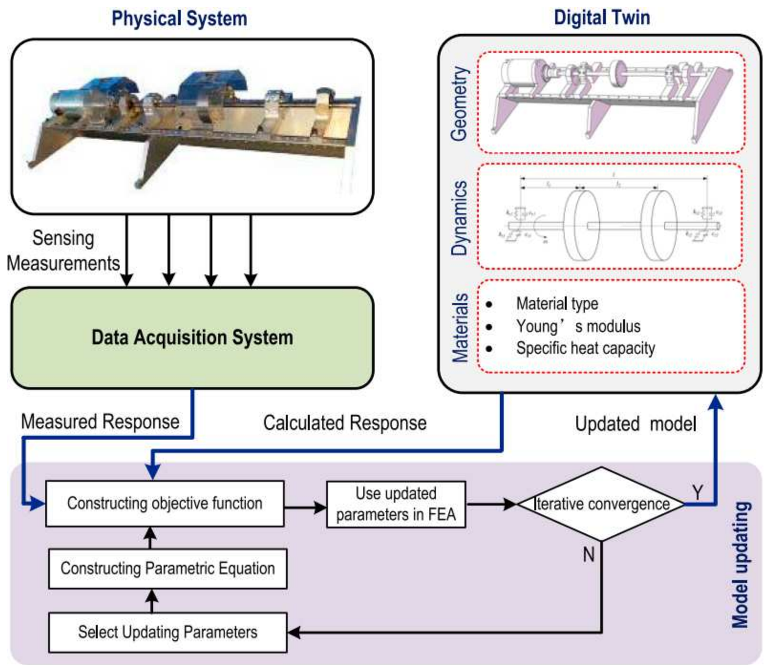


Figure 47. Digital twin model for a rotating system [96].

Xu et al. [97] suggested employing a digital twin approach based on deep transfer learning from fault diagnosis. The approach was deployed in two phases. First, a high-fidelity virtual model was explored to identify potential problems and train a deep neural network diagnostic tool. Then, the trained diagnostic was transferred to the physical system for real-time monitoring and predictive maintenance. The proposed approach was employed in a car-body production line (Figure 48). Through the dual fault diagnosis — in virtual and physical space — the risk of accidental breakdown was greatly reduced, making smart manufacturing sustainable, reliable, and efficient.

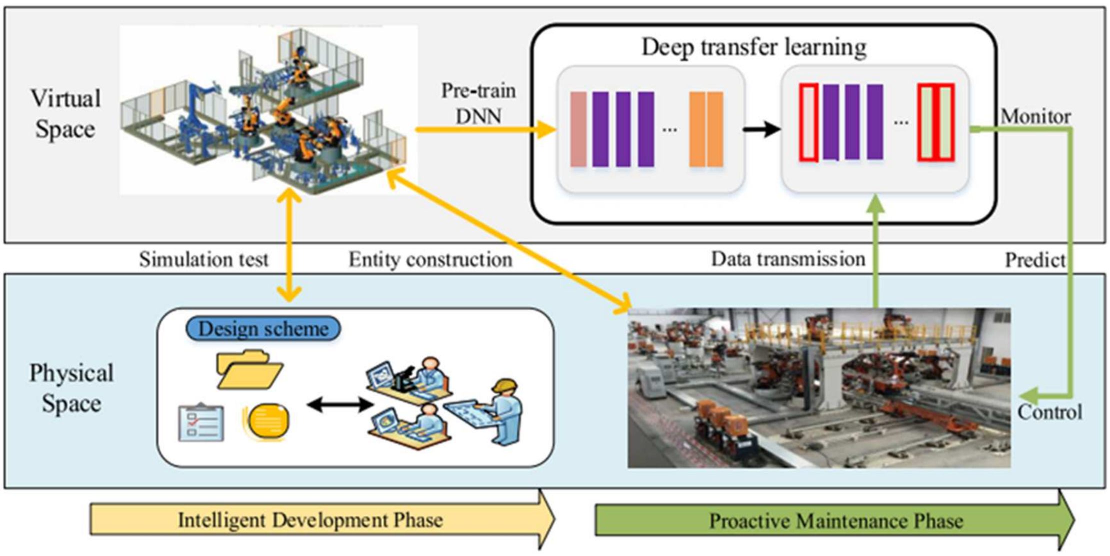


Figure 48. Conceptual view of the digital twin based on deep transfer learning [97].

Xia et al. [98] explored the capabilities of a digital twin to train deep reinforcement learning agent for smart manufacturing plants, and developed a control methodology, named Digital Engine, to schedule manufacturing tasks, identify optimal actions, and demonstrate control robustness.

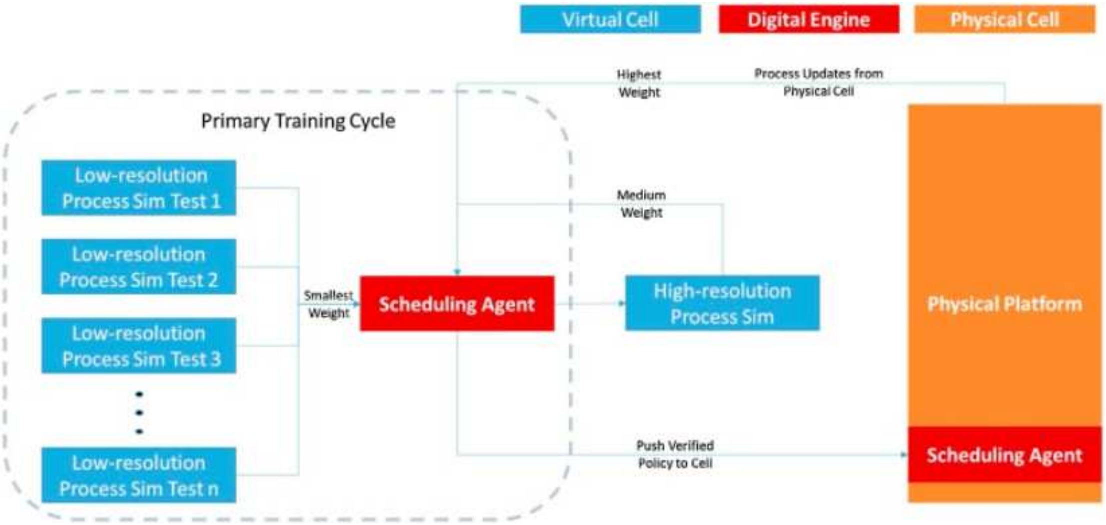


Figure 49. Architecture of the digital engine [98].

Wang et al. [99] developed an innovative digital twin to monitor and control welding processes during manufacturing. The digital twin was developed to visualize a digital replica of the physical welding for joint growth monitoring and penetration control. The digital twin was exploited in a decision-making strategy to meet quality requirements. According to the authors their methodology can be further improved by including additional parameters in their digital twin, such as heat transfer, fluid flow and joint microstructure based on advanced sensing and computational intelligence.

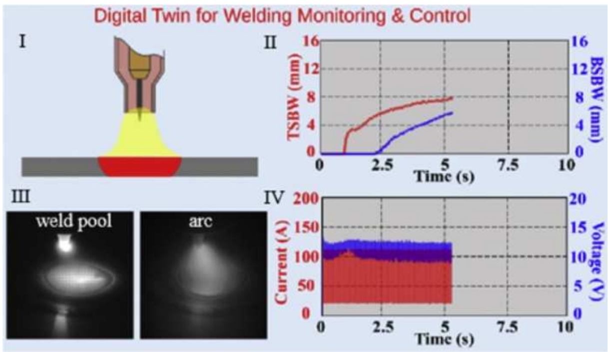


Figure 50. Digital twin to monitor and control welding process [99].

Booyse et al. [100] proposed the concept of deep digital twins for detection, diagnostics and prognostics. The system was constructed from deep generative models which could learn the distribution of healthy data directly from operational data at the beginning of an asset's life-cycle. This approach had the benefit that it did not rely on historical failure data to produce an estimation of asset health. The authors demonstrated that the system was able to detect incipient faults, track asset degradation and differentiate between failure modes in both stationary and non-stationary operating conditions when trained on only healthy operating data.

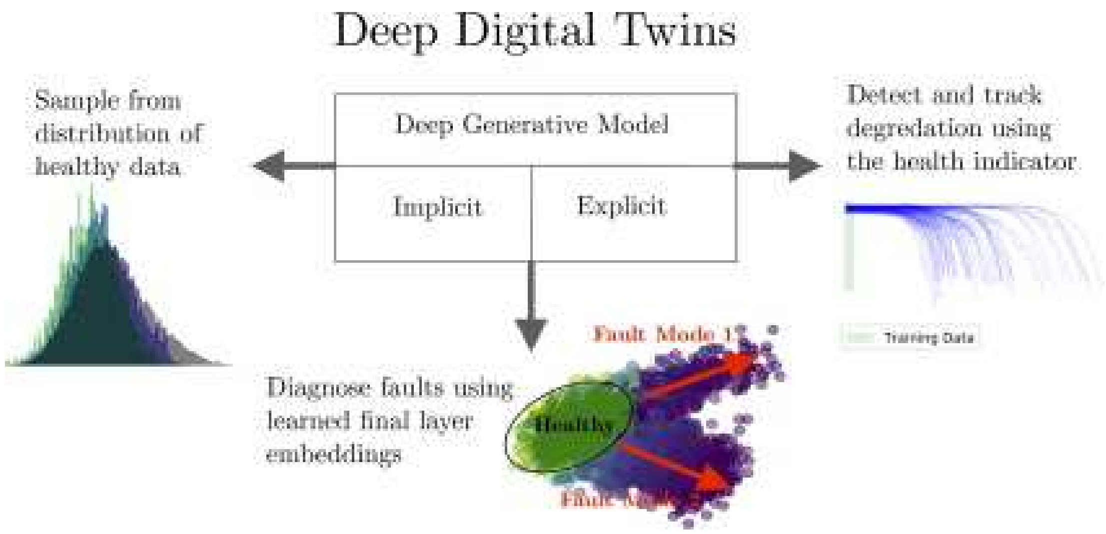


Figure 51. Deep digital twins for detection, diagnostics and prognostics; courtesy of [100].

Franciosa et al. [101] employed digital twins targeting quality improvement. The benefits of their approach were (i) faster selection of process parameters; (ii) capability to automatically adjust process parameters by leveraging stochastic uncertainty; and (iii) real-time closed-loop control with adaptive selection of new set of process parameters.

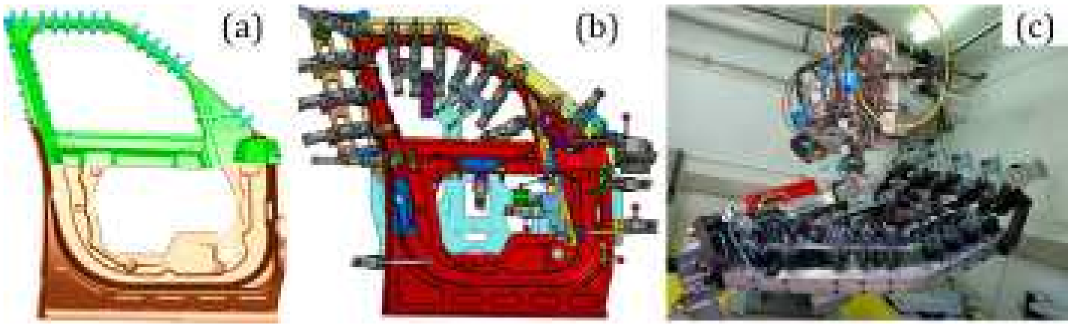


Figure 52. Digital twin for quality improvement [101]. (a) concept; (b) detailed; (c) pre-production.

Zhang et al. [99] proposed intelligent process planning for digital twin manufacturing cell based on deep learning. According to their approach a deep residual network is first employed as the base architecture for the framework. The neural network could “understand” the design goals in a drawing or a 3D CAD model via its views and automatically retrieve relevant knowledge for the quick generation of theorical processes. Then, an evaluation twin was constructed to transform the theorical processes into practical operations and produce an optimal process plan. Finally, a test bed of the framework could be constructed to demonstrate the feasibility and effectiveness of the approach.

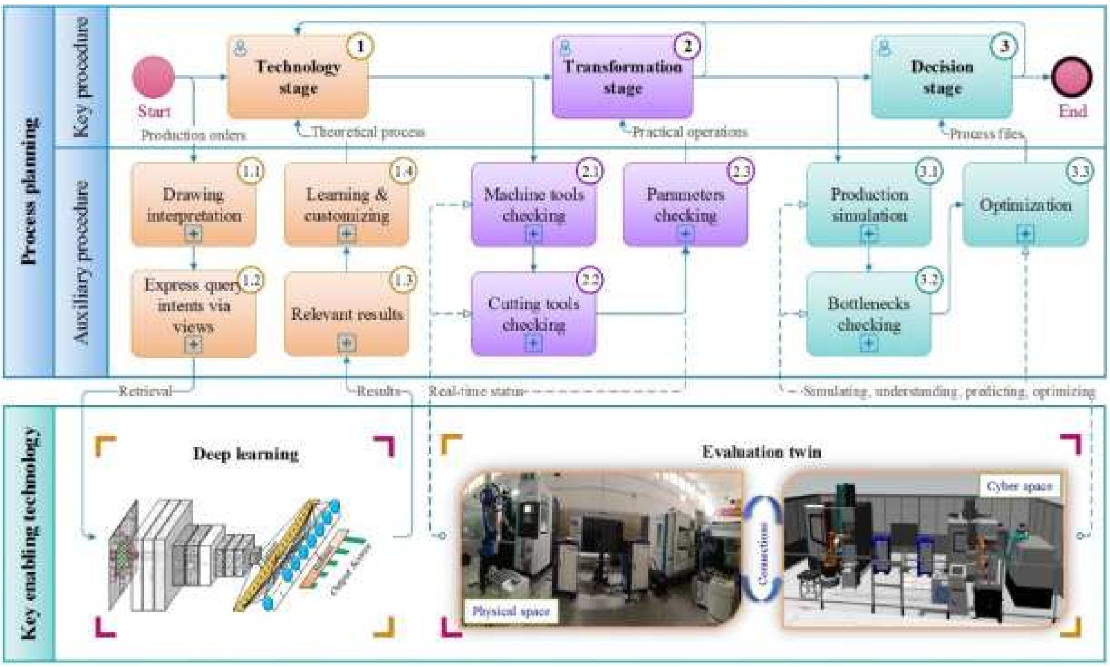


Figure 53. Framework of intelligent process planning [99].

Ali et al. [102] employed deep learning based semantic segmentation of μCT images for creating digital material twins of fibrous reinforcements, enabling the use of AI in finer manufacturing scales. A deep convolutional neural network was employed to generate the digital twin of 2D glass and 3D carbon fiber reinforcements.

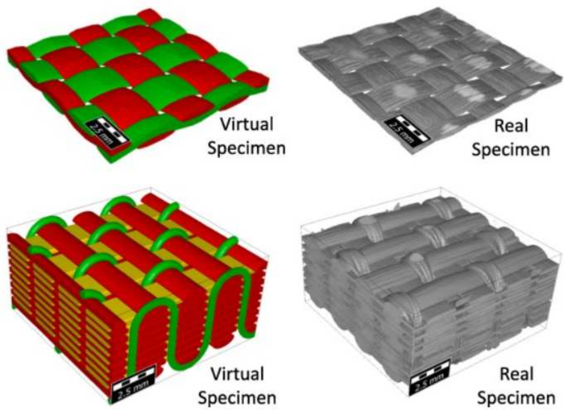


Figure 54. 3D visualization of the virtual and real specimens of 2D plain weave glass, and 3D orthogonal carbon fabrics [102].

3.5.3.4 2021

A typical problem in manufacturing systems is that acquired signals have different time scales. Chakraborty and Adhikari [103] presented a digital twin model based on machine learning for such dynamical systems with multiple time-scales. The proposed model had two components: (1) a physics-based data processing component, and (2) a learning component for the time evolution of the system, based on machine learning.

3.5.4 AI-enhanced IoT

Internet of Things (IoT) and their industrial counterpart (IIoT) can be thought of as internet-aware networks of smart devices like sensors and actuators. IoT and IIoT technologies can be employed in various applications facilitating real-time monitoring, analytics and decision support systems [104], and play, therefore, an important role in the general concept of Industry 4.0.

A typical Industrial IoT architecture consists of the following components [105]:

- **Things:** All industrial devices that need to be monitored by an Intelligent Edge Gateway.
- **Intelligent Edge Gateway:** The software which interconnects Things and IoT Cloud.
- **IoT Cloud:** This is the central platform of information, which collects gathers data and applies AI/ML techniques.
- **Business Integration and Applications:** This refers to application systems that are important for planning and scheduling production.

There are four main categories of data that are used in IoT projects [106]:

1. **Measurement data:** Physical parameters that are being monitored by sensors.
2. **Event data:** unexpected incidents or important status changes of systems during operation.
3. **Interaction and transaction data:** Data related to the inter-device communication, and human-device communication.
4. **Diagnostic data:** Data about structural and operational health of mechanical systems and processes.

Depending on the expected result there are three data analysis categories [105]:

1. **Descriptive data analysis:** Organizing and management of data to provide a clear overview of the production line functionality.
2. **Predictive analysis:** Prediction of faults before their occurrence by applying AI analytics.
3. **Prescriptive analysis:** Proposal of solutions for any possible predicted fault.

3.5.4.1 Frameworks and platforms

Various IoT platforms are already available for applications in smart industry. Kamath et al. [107] have reviewed the following open-source platforms:

- **Eclipse Hono** [108] provides interfaces that can be used for the connection and interaction of numerous IoT devices independently of their communication protocol.
- **Eclipse Ditto** [109] is about a framework that supports IoT Digital Twins software pattern implementation.

- **Apache Kafka** [110] is proposed for real-time streaming applications. It records, stores and processes the acquired data, enabling the building of data pipelines.
- **Influx DB** [111] is a real time series database -easy to setup and use- that can be used to store multiple data types over a time period. It is capable to handle million writes per second.
- **Grafana** [112] is analytics and monitoring solution. It provides data source models and support for many time-series databases. It also enables users to visualize and trigger alerts based on metrics from multiple stored locations.

etc.

An interesting approach is the called SWoTI [113] platform, composed of different layers. Each of these employs a variety of tools and techniques to build smart applications that can process raw sensory data and support smart manufacturing. The overall architecture is depicted in Figure 55.

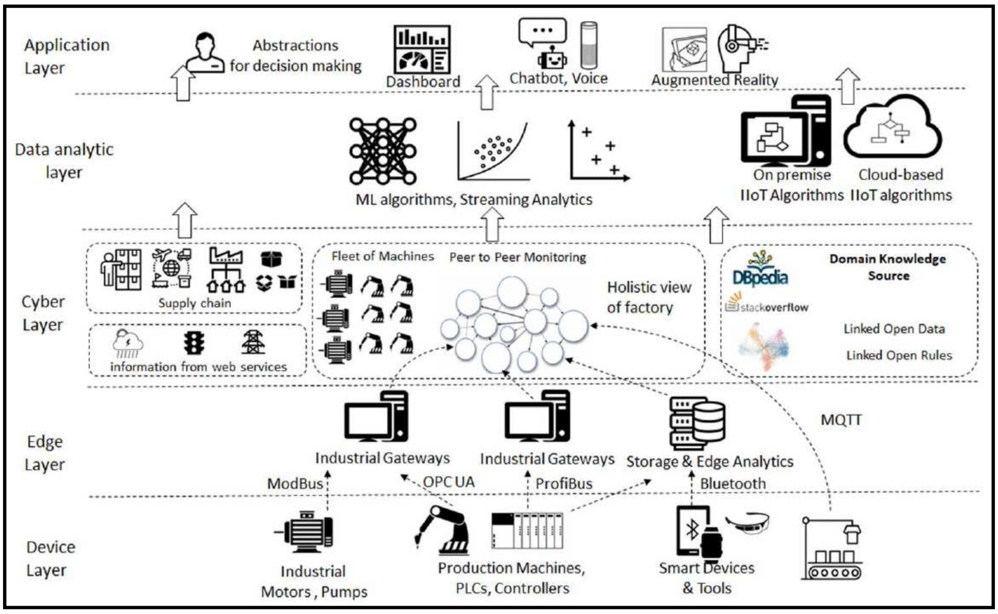


Figure 55. A layered view of the Semantic Web of Things for Industry 4.0 (SWoTI) platform [113].

The layers of this platform are briefly described in the following paragraphs:

- **Device Layer** contains all tools, devices, machinery and equipment employed in an industrial production process.
- **Edge Layer** transforms the collected data into information using analytics-based methods and techniques, and enhances the interoperability between devices.
- **Cyber Layer** operates as a collective information hub, which prepares data for the data analytics layer. This layer manages a massive amount of data collected by various distributed sources inside and outside the industry. Data ranges from the production process to the supply chain, offering that way an overview of the available information. According to the authors, an alternative technology solution in that layer could be a

decentralized and distributed across peer-to-peer sync blockchain network, where each participant could have data access in order to process them independently. a blockchain [114] is considered a distributed, decentralized and constant system that keeps the information and data of the various transactions that may occurr in a specific person-to-person network.

- **Data analytics layer** identifies underlying relationships among the collected data by applying AI-based industrial analytics algorithms. This way, it enables decision-makers to make optimal decisions.
- **Application Layer** creates customized applications by using a wide variety of ML approaches, exploiting the data collected by previous layers. This layer is primarily concerned with the presentation and visualization of the acquired knowledge to the users of the system.

3.5.4.2 Embedded software and edge devices

TinyML [115] is one of those recent developments in AI that enables the use of machine learning and deep learning on embedded devices. The popular TensorFlow (TF) library has been ported (TF Lite) to mobile and IoT applications [116] and platforms; Arduino Nano BLE SENSE and IoT [117,118], the Sparkfun edge [119] etc. are low-cost edge devices that can run SoA ML algorithms without the need for high-end processing systems. It must be noted though, that only trained DNNs can be run on such light-weight platforms; algorithm development and training still remains a complex and computationally demanding task, and heavily relies on high-end systems such as servers and cloud/fog computing. IoT sensor networks can benefit from the emerging Blockchain technologies [120,121] as a decentralized architecture for secure and reliable data sharing among nodes.

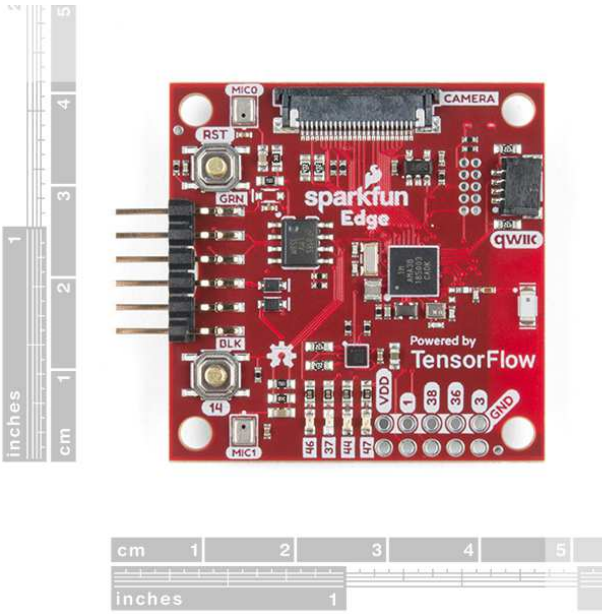


Figure 56. Sparkfun Edge; Power by TensorFlow [119].

The arrival of MicroPython [122] opens new ways for miniaturized smart devices. MicroPython is a Python 3 flavor optimized to run on microcontrollers. AI code can be developed on a PC and then transferred to a microcontroller, such as the PyBoard (Figure 57). This way, data acquisition, processing and decision making can take place on-site and in real-time. Of course, efficient AI algorithms are needed to make a robust machine learning model fit into the limited hardware of a microcontroller.

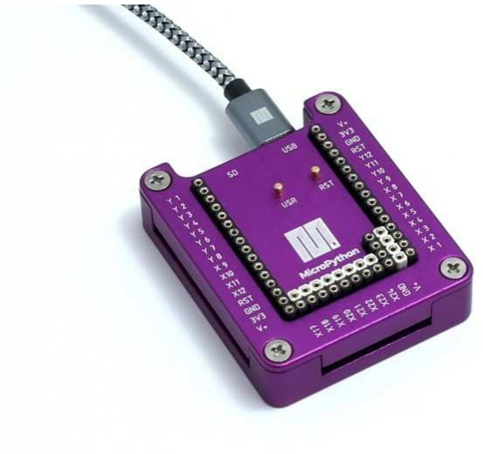


Figure 57. PyBoard [122].

Digital Twin has demonstrated great value for smart factories in Industry 4.0. AIoT can be a critical part of implementing digital twins where the connected sensors and actuators can collect real-time data from production lines and send them to the digital twin running in the cloud. Moreover, AI technologies can enable an intelligent analysis of data and help to make smart decisions.

3.5.4.3 Uses and applications in Industry 4.0

A service-oriented digital twin model is proposed in [123], which uses an ontology-oriented knowledge structure to represent the knowledge about the manufacturing system from the sensing data. It also designs a vocal interaction system for knowledge retrieval based on speech recognition and text-tospeech synthesis. In [124], a knowledge graph-based digital twin model is introduced which is composed of four parts, i.e., feature extraction, ontology creation, knowledge graph generation, and semantic relation extraction. It can extract and infer knowledge from large scale production line data and enhance manufacturing process management via semantic relation reasoning. Real-time scheduling (RTS) in the smart factory is another hot research topic. In [125] a reinforcement learning-based RTS model is proposed, which can incrementally update and maintain the knowledge base in RTS during operations to respond to shop floor environment change.

A typical example of AIoT application in the smart industry is the Printed Circuit Board (PCB) manufacturing. There are three scenarios that are related to AIoT systems with different sensors and devices, i.e., manufacturing, visual defect inspection, and machine fault diagnosis. First, industrial robots have been widely used in the production line of smart factories, e.g., for drilling and grasping. AI technologies can be used to improve their functionalities. For example, Bousmalis et al. propose a deep robotic grasping model named GraspGAN [126], which bridges the domain gap between synthetic images and real-world ones via the pixel-level image translation and a feature-level domain classifier. To increase the safety, speed, and accuracy of autonomous picking and palletizing, Krug et al. propose a novel grasp representation scheme allowing redundancy in the gripper pose placement [127]. Second, PCB defect inspection carried out by workers manually is laborious and time-consuming. Recently, deep learning-based methods have been proposed for automatic real-time visual defect inspection [128]. Third, it is important to predict and diagnose machine faults from sensor data to reduce PCB defects, thereby increasing production efficiency and reducing losses. Although the digital twin system provides a useful mirror virtual environment for creating and testing new equipment and models, it is still challenging to fast adapt the trained model or control policy to the physical world. Thereby, more efforts should be made in the areas of domain adaptation, transfer learning, and mete-learning. Besides, since it is difficult to collect and annotate edge samples in the industrial context, zero-/few-shot learning is also worth further study. In addition, causal analysis of the product defects based on data and knowledge is also of practical importance.

3.5.5 AI for computer vision

Computer vision is the field of artificial intelligence that trains computational systems to visually interpret the real world. This means that computers should be able to identify objects and patterns by processing digital images, videos etc. using artificial intelligence techniques. Computer vision can be further extended to object classification (e.g., identify an object in an image) and instance segmentation (e.g., identify multiple objects of the same class within the same image).

3.5.5.1 2015

Yoo [129] conducted a review on deep learning techniques and more specifically on Deep Convolutional Neural Networks (DCNN) in the field of object recognition. Emphasis was mainly given to those employed in GoogleNet network. This review paper highlighted Deep learning techniques as significant and promising approaches for recognition tasks, outperforming other conventional methods in this realm.

Shanmugamani et al. [130] employed various classifiers based on Bayes, ANN and SVM for the detection and classification of surface defects of used gun barrels, under the scope of proposing a computer vision-based approach. A total of 1000 images were initially split in 5 classes of defects and then multiple textural features were selected to train the classifiers, finally evaluating their accuracies. Among the tested classifiers, SVM showed the best accuracy of 96.67%, emerging as the best classifier for this application.

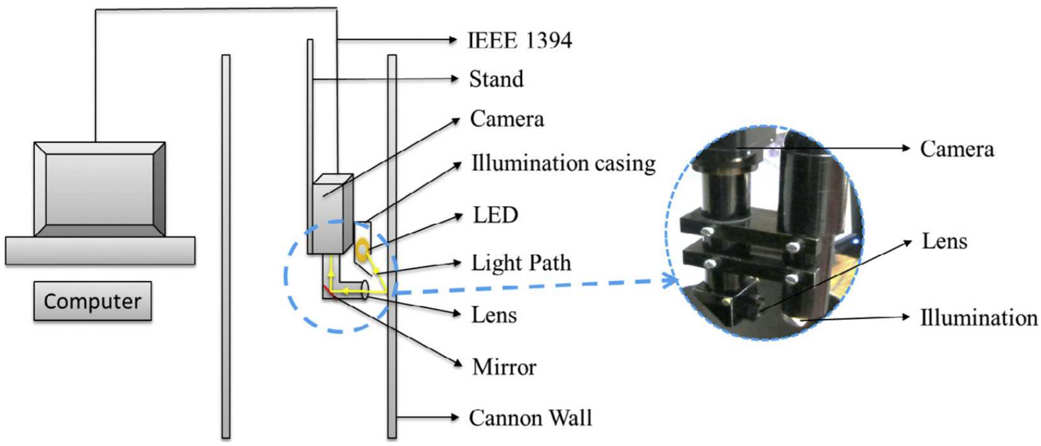


Figure 58. Schematic diagram of experimental set up.

3.5.5.2 2016

Ondruska and Posner [131] propose a new method of unsupervised training for deep object tracking directly from raw sensor data. For this purpose, a four-layers feed forward Recurrent Neural Network (RNN) was utilized to learn a mapping from sensor measurements which were provided by a planar laser scanner using a 2D grid of 50x50 pixels. The whole process showed a considerable learning and prediction efficiency of the proposed network, having the capacity to perform well in a variety of future scenarios.

Islam et al. [132] explored several Deep Learning models in the field of computer vision, hence applying AlexNet and VGG_S models on different datasets belonging to five different application areas, such as object, event, scene, expression and gender classification, to evaluate their efficiency. Considering remote sensing scene classification, authors proceeded to a comparison between the two models as well as with other state-of-the-art to assess their overall performance. In most of the cases, VGG S outperforms AlexNet model in the training phase, reaching a recognition rate of up to 93,3%, whereas their performance on certain datasets is better than the existing state-of-the-art deep learning models.

Schwartzman et al. [133] employed state-of-the-art image classification techniques based on deep neural network architectures to significantly improve the identification of highly boosted electroweak particles produced by collision events at the Large Hadron Collider (LHC). For the purposes of image processing and computer vision tasks, they introduced a new data representation, namely the jet-image, which is defined by a 25x25 grid of size (0.1x0.1). Two different architectures of deep neural networks for image classification, Convolutional Neural Networks (CNN), and Fully Connected (FC) MaxOut networks, were trained to separate W (signal) and QCD (background) jets. The results of this study showed that deep neural networks classifiers significantly outperform state-of-the-art classification methods thus, providing new ways to visualize the information learned by the DNNs.

3.5.5.3 2017

DeCost et al. [134] proposed a system for classifying powder materials by employing machine learning methods in the domain of metal additive manufacturing. Feature detection and description algorithms were applied to cluster, compare, and analyze powder micrographs, whereas a Support Vector Machine (SVM) classifier was utilized over the training and validation set of the micrographs collected. The proposed computer vision system achieves a classification accuracy of more than 95%.

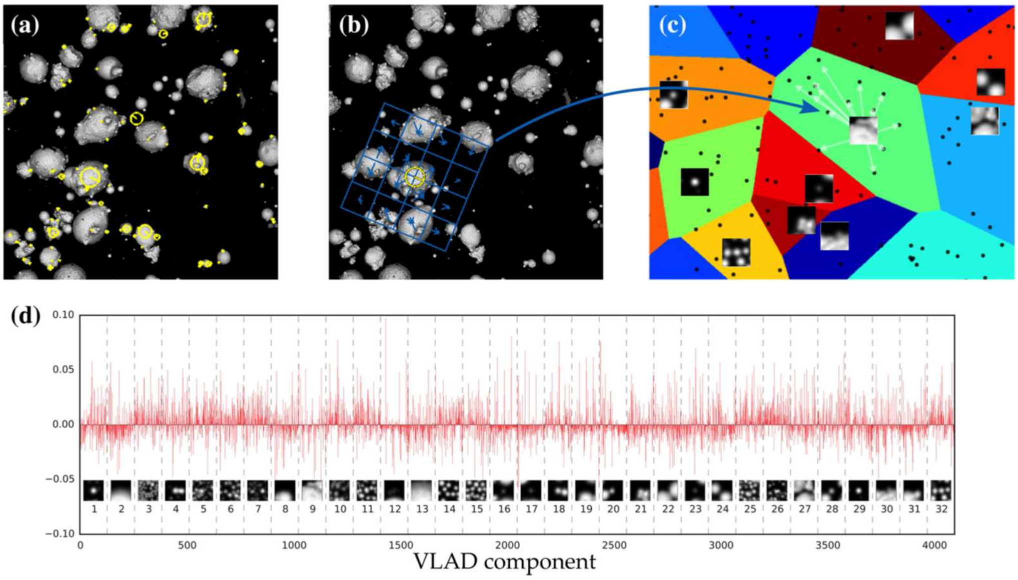


Figure 59. Schematic diagram illustrating the construction of SIFT-VLAD microstructure representations [134].

Mery & Arteta [135] explored several CNN models for the task of automatic defect recognition in automotive components, using a dataset of 47.500 cropped X-ray images of 32x32 pixels. After a comparative analysis and evaluation of 24 computer vision techniques (including deep learning), the best performance was achieved by a simple Local Binary Pattern (LBP) descriptor with a SVM-linear classifier obtaining 95.2% of accuracy.

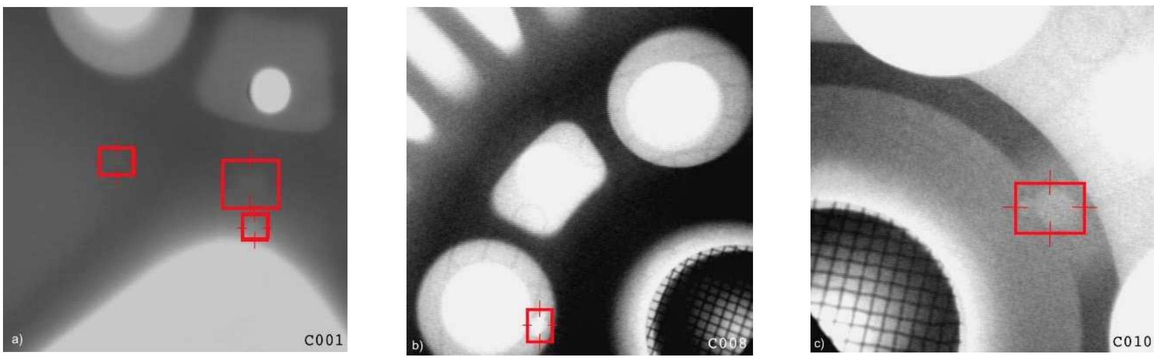


Figure 60. Examples of defects in real X-ray images of wheels from GDXray dataset [135].

García-Ordás et al. [136] proposed a new computer vision approach for classifying tool wear by employing a machine learning classification model. They Implemented a new shape descriptor able to capture image information, while using a dataset of greyscale images of 53 tools. The descriptor which utilized a SVM classifier, was compared to two other classifiers, demonstrating its performance superiority against other descriptors. The results showed accuracy values between 80.24% and 88.46% in the scenarios conducted.

Figure 61. Image capture prototype. The support in which the camera is placed and the LED bars employed are shown [136].

Wu et al. [137] discuss in their paper the application of certain deep learning algorithms, such as Convolutional Neural Networks (CNNs) and Fully Convolutional Networks (FCN) in computer vision. They pay attention to the advantages of deep learning in this field, especially to their strong capacity in feature extraction, comparing them to traditional machine learning.

In their work, Vakharia et al. [138] explored textured surface image identification methodology employing SVMs and ANNs, as being promising Artificial Intelligence techniques used for classification, or identification in fields like fault diagnosis and manufacturing. Grey scale images converted through a 2D wavelet transform were used as the input dataset. The texture characterization efficiency for training using SVMs and ANNs reached 100%.

Birlutiu et al. [139] proposed an innovative system based on machine learning that performs an automated defect detection in porcelain products. It is based on a Convolutional Neural Network (CNN) and uses a dataset containing grey scale images resized to 28x28 pixels. Several algorithms were compared and the best results were obtained using the CNN architecture, while the SVM comes with a slightly lower performance.

3.5.5.4 2018

Maggipinto et al. [140] test the performance of the proposed CNN-based model, which is considered the foremost choice for common vision problems such as object recognition. The CNN which used the 2D version of the input dataset of a 50x54 dimension, is capable of providing an effective handling of data without requiring any explicit features extraction. The proposed model was further compared with other non-DL approaches which are common in semiconductor manufacturing, exhibiting a better performance.

Silva et al. [141] introduced Machine Vision System (MVS) as a means to increase detection in quality control inspection, while they explore the main concepts and applications of the AI domain to Industry 4.0. They are in search of a method that could select the best AI framework for each kind of solution. However, the existing MVS solutions applied could improve quality inspection through the integration of AI technologies.

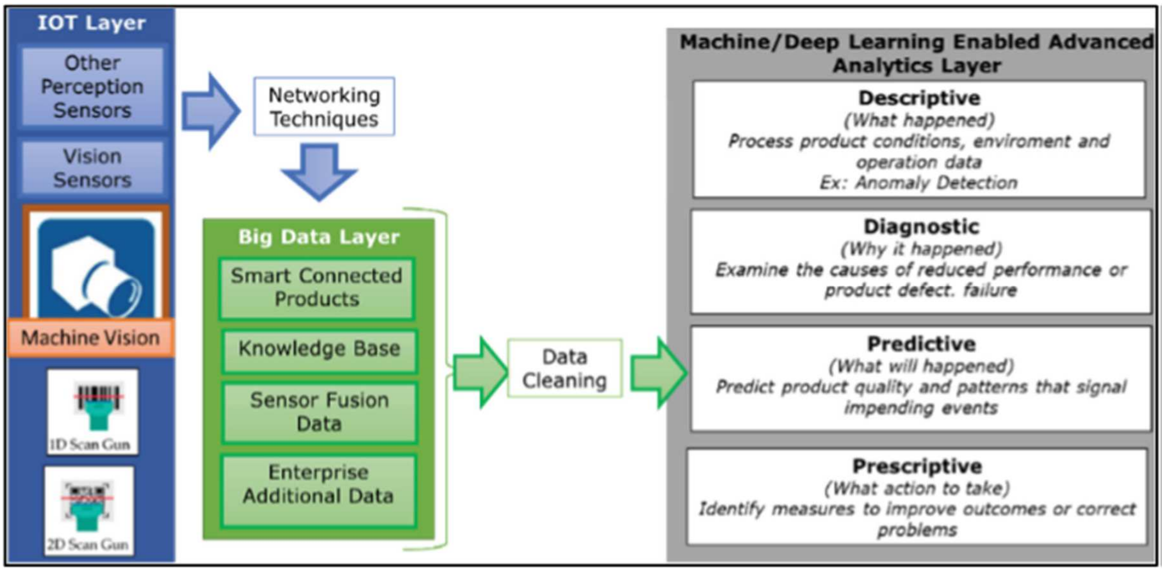


Figure 62. MVS integrated with a simplified 4.0 Industry diagram [141].

Nguyen et al. [142] implemented a hybrid machine learning-based approach that performs classification of possible reduced order models. In the field of mechanics of materials, model recognition is achieved through the application of a CNN on a digital image of the mechanical test, after a 2D digital image and a 3D voxel image are inserted as required inputs. The proposed framework exhibits satisfactory prediction accuracy regarding the overall quality of the process.

Arents et al. [143] proposed a model for automation of industrial tasks, that integrates 3D computer vision, artificial intelligence algorithms and industrial robots. The experimental system consists of Kinect V2 RGB+Depth camera of resolution 1920x1080 and Universal Robots UR5, providing multiple motion planning packages and algorithms The computer vision software includes two components, namely: Object detection and Object classification. In the second case, a CNN is deployed when the robot picks the object.

3.5.5.5 2019

Feng et al. [144] employed deep convolutional neural networks to achieve high-speed 3D imaging. They combined deep learning with profilometry using the structured light illumination. Upon proper training, the system could convert fringe images to 3D shapes at a rate of 20,000fps.

Liu et al. [145] employed deep learning for real-time 3D surface measurement in additive manufacturing. Their method consisted of a supervised deep neural network for image analysis. The key idea was to find a correlation between 2D images and 3D point cloud data; this was achieved using a convolutional neural network.

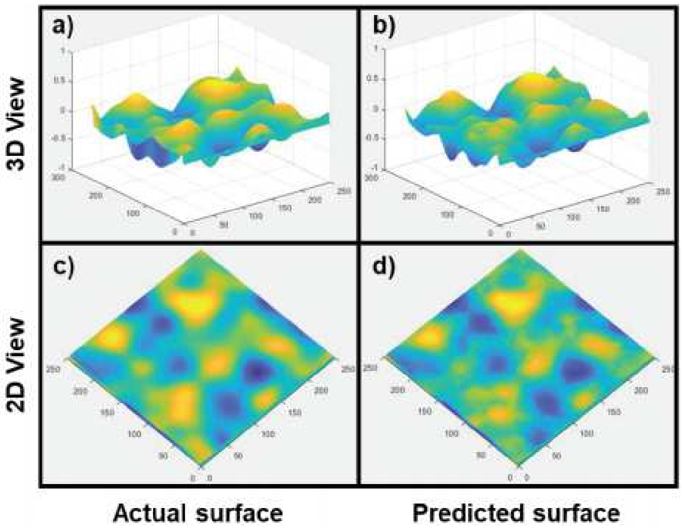


Figure 63. Comparisons of actual and predicted surface for the proposed real-time 3D surface scanning method[33].

He et al. [146] proposed a technique utilizing machine vision methods in order to capture the geometric information of a manufactured object during an Additive Manufacturing process such as FDM (Fused Deposition Modelling). More specifically, a non-contact methodology was developed to obtain the image and the state of each printed layer and with the aid of image processing algorithms, the geometrical characteristics of the part were measured. The results of laboratory experiments showed the efficiency of the suggested methodology.

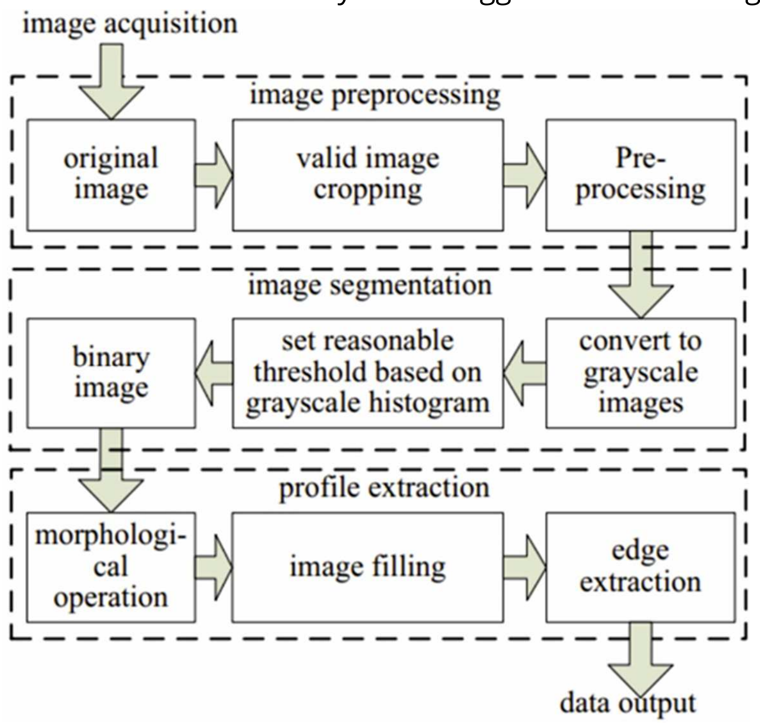


Figure 64. Illustration of the image processing methodology [146].

3.5.5.6 2020

Kwon et al. [147] employed deep neural networks to analyze laser images and assess the quality of microstructure in metal sheets. They attempted to correlate the microstructure of the material to the laser power and pixel intensity. The proposed model exhibited as hit rate over 98.9% in classification.

3.5.6 AI for augmented reality

3.5.6.1 2018

Yin et al. proposed an automatic interaction method using part recognition based on deep network for assembly guidance with augmented reality [148]. By recognizing the assembly part, the augmented assembly guidance information of the corresponding parts assembly process could be triggered in real-time without direct user interaction. Experimental results showed precision around 94% on average, at a recognition rate 200ms per image.

Bernstein et al. suggested reinforcement learning for computer vision and robot navigation [149]. This way, a robot could become "visually aware" of its physical environment in a self-supervised manner, and navigate in space avoiding any obstacles.

3.5.6.2 2020

Park et al. [150] proposed a smart and user-centric task assistance method, which combines deep learning-based object detection and instance segmentation with wearable AR technology; the proposed approach is based on the use of HoloLense [151] and provides more effective visual guidance with less cognitive load.

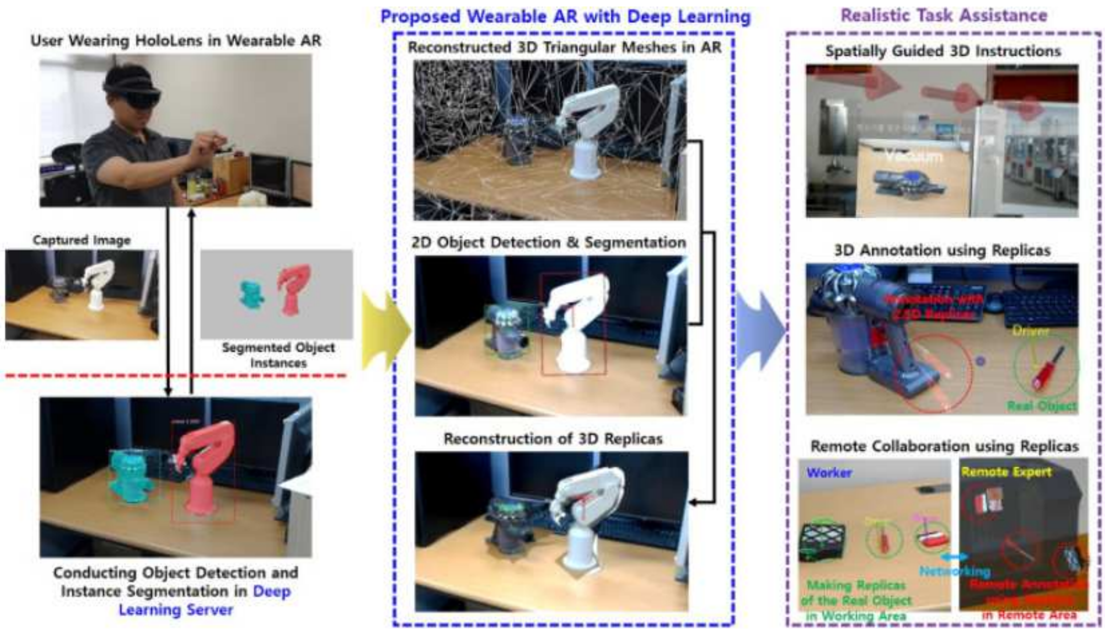


Figure 65. Overview of the proposed wearable AR approach for smart task assistance [150].

According to the authors, the 2.5D and 3D replicas can be effectively used for 3D annotation and information sharing. The performance of the apparatus was assessed within a realistic manufacturing task-related user study involving the inspection and maintenance of a 3D printer. The proposed approach did not require a significant user effort, and it was favorable for the performance of various tasks in wearable AR. Despite their success, the authors still see room for further improvements. Current implementation requires close distance to identify the object and create the required mesh; especially if the object has a reflective surface. Rapid motion is still an issue, as it may create blurry and generally distorted images. The matching between the physical and virtual object can be improved.

Figure 66. HoloLens [151].

Park et al. [152] developed a methodology for mobile augmented reality based on deep learning, which targets task assistance using 3D spatial mapping and snapshot-based RGB-D data. The proposed method extracted 3D point cloud data corresponding to a real object from snapshot-based 3D point cloud data. The virtual model was spatially mapped to the real object by the 3D position and pose of the real object. The authors claimed that the proposed approach was more efficient than the typical AR marker-based approach concerning accuracy and task performance as well as qualitative evaluation.

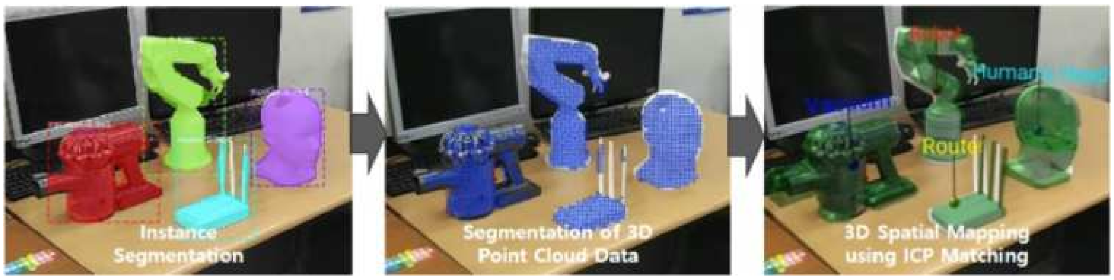


Figure 67. Demonstration of the deep learning-based 3D spatial mapping [152].

Rabinovich et al. [153] patented a head-mounted augmented reality device, which incorporated a hardware processor programmed to receive different types of sensor data from various sensors (e.g., inertial sensors, depth sensing camera, eye imaging camera, microphone, etc.). The device could determine a variety of "events", such as gesture identification, semantic segmentation, object detection, lighting detection, simultaneous localization and mapping, etc.

Wang et al. [154] described a framework for implementing smart manufacturing shop floor systems based on the ubiquitous augmented reality. The proposed system made use of data sharing between shop floor resources and a sensor network in order to perform real-time optimization of the production schedules. Using the proposed framework, the operators were able to receive information, instructions and guidance from the experts and manufacturing systems, and to update the systems on task parameters, such as estimated completion times, progress and machine status.

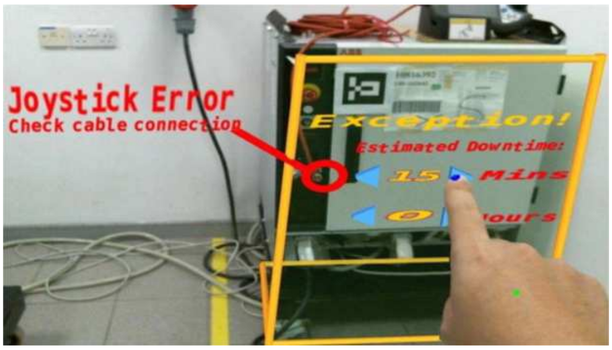


Figure 68. Demonstration of ubiquitous augmented reality system [154].

Upadhyay et al. [155] proposed a framework combining machine learning for object detection and product identification, and augmented reality for an improved user-experience. TensorFlow, MobileNets and SSD were used for object detection, while Vuforia was employed for object identification.

Lai et al. [156] developed a smart augmented reality system to provide workers instructions during mechanical assembly processes. The system was based on regional convolutional neural networks, trained to identify tools using CAD models. The system led to significant reduction of assembly times and errors, compared to traditional methods (paper manual instructions).

Figure 69. Augmented reality system using convolutional neural networks to guide workers during assembly process [156].

3.5.7 AI for quality control

It has to be noted, that the production of high-quality end-products coupled with minimum cost is a high priority manufacturing task. Industry 4.0 has already exhibited its potentials via the utilization of core technologies such as AI and Machine Learning in order to reach the abovementioned goals more successfully than ever. Data mining has become a worthwhile resource and the acquisition as well the store of data are cheaper compared to previous decades. Therefore, through the employment of process-based machine learning algorithms, manufacturers could utilize data to enhance product quality and production's efficiency.

3.5.7.1 2015

Lipiński and Majewski [157] implemented an innovative and interactive hybrid system which is very important for the development of new effective manufacturing methods, providing monitoring and optimization tasks. This approach contains neural networks for forecasting the state of the tool and its surface quality. In terms of quality control, the neural models have been developed for a subsystem for detection of inaccuracies and optimization of machining parameters.

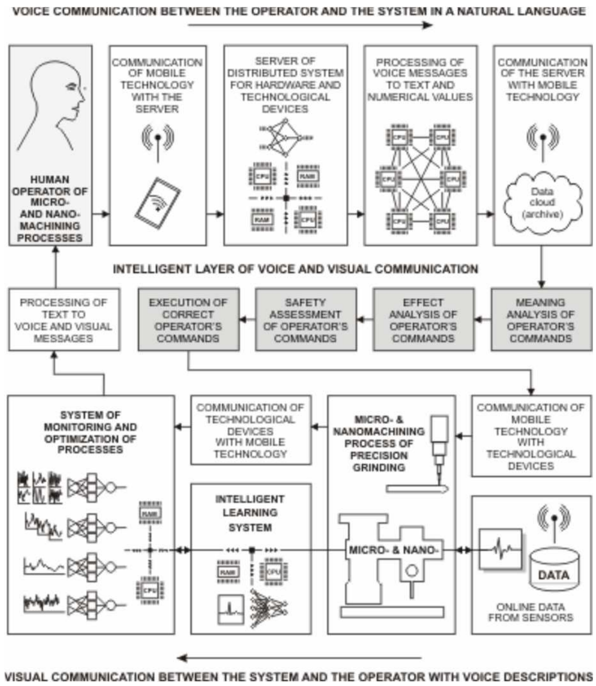


Figure 70. Interactive system for monitoring and optimization using mobile technologies [157].

3.5.7.2 2016

Devarasiddappa et al. [158] developed an ANN model for surface roughness forecasting in a wire-cut electrical discharge machining (WEDM) system for an aerospace alloy. In specific, a multi-layer feed forward ANN architecture 4-16-1 working on gradient descent back propagation algorithm was implemented and was found optimum. The predictive performance of the ANN model was tested using random experimental dataset recording a prediction accuracy of 93.62%.

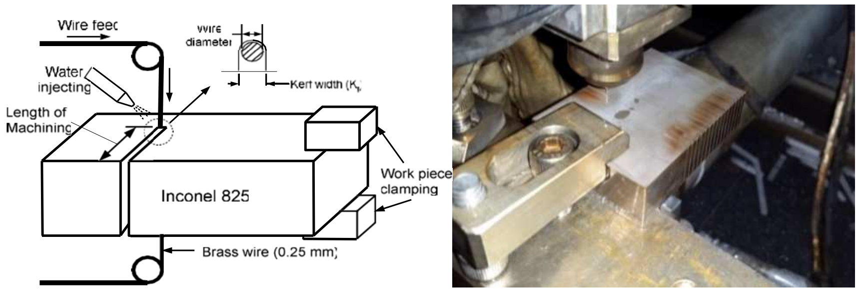


Figure 71. Wire-cut electrical discharge machining (WEDM) system (a) Schematic arrangement (b) Experimental set up [158].

Purnomo and Dewi [159] proposed a model for the prediction of manufacturing quality using Interval Type-2 Fuzzy Logic (IT2-FL) which is able to handle several ambiguity and uncertainty factors in the quality level of production, which can't be modelled using formal mathematical models. The proposed approach implements a two-stage forecasting model to predict material, process and final product quality in the first leg and manufacturing quality in the second leg. The accuracy achieved for each stage reaches 90%, making this assessment model quite promising for manufacturing systems.

3.5.7.3 2017

Wu et al. [55] introduced a random forest based prognostic technique for predicting the tool's wear in machining operations. The results showed that the utilized algorithms demonstrated better performance compared to more classical machine learning methods like feed-forward back propagation artificial networks. The inputs for the development of the algorithms were collected from cutting forces, vibrations and acoustic emission during the material removal process. The authors declared that in future work, they will focus on applying these techniques in large-scale and real-time prognosis.

3.5.7.4 2018

Scime and Beuth [160] presented a multiscale convolutional neural network for autonomous anomaly detection and classification in laser powder bed diffusion additive manufacturing. The proposed neural network could learn the anomalies and other key information at multiple size scales. The authors claimed that the proposed network was more efficient than previous methodologies.

In Vafeiadis et al. [161], an early stage-decision support system was utilized to inspect printed circuit boards and investigate the inference faults due to the deposition of excess glue on the board. More specifically, a pixel-wise vector of the inspected areas was applied coupled with various state-of-the art machine learning algorithms to evaluate the efficiency of the proposed defect detection system. The results exhibited that Support Vector Machine (SVM) polynomial classifier achieved the best performance.

3.5.7.5 2019

Lin et al. [162] proposed a cascading convolutional neural network for the detection of defects on steel surfaces. Quality control was performed in two stages. First, modified "single shot multibox detector model" was used to learn possible defects, and then, deep residual network were employed to classify three types of defects, namely rust, scar, and sponge. The model was experimentally assessed using industry datasets and exhibited high precision and recall scores.

Lin et al. [163] employed a deep convolutional neural network to automatically detect defects on LED chips. The authors attempted to introduce a methodology that alleviates the shortcomings of existing methods, namely, they tried to reduce complexity of the model, increase robustness, and reduce the amount of required resources (financial, labor and time) for chip inspection. The introduced "LEDnet" was assessed experimentally and its accuracy was around 95%. The simplicity of the network came from the fact that it did not need complex image preprocessing nor training from human experts. A major limitation, according to the authors, was that LEDnet could identify only specific type of defects, and could not generalize; this limitation could be dropped in the future by enhancing the training process with proper image collections.

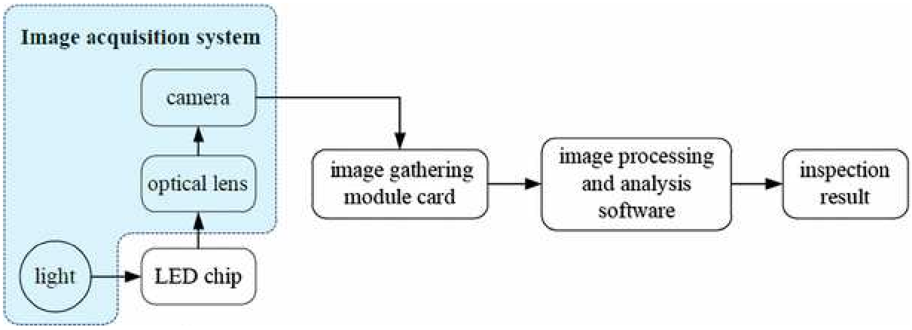


Figure 72. Concept of automated defect detection on LED chips using CNNs [163].

Liu et al. [145] employed deep learning for real-time 3D surface measurement in additive manufacturing. Their method consisted of a supervised deep neural network for image analysis. The key idea was to find a correlation between 2D images and 3D point cloud data; this was achieved using a convolutional neural network.

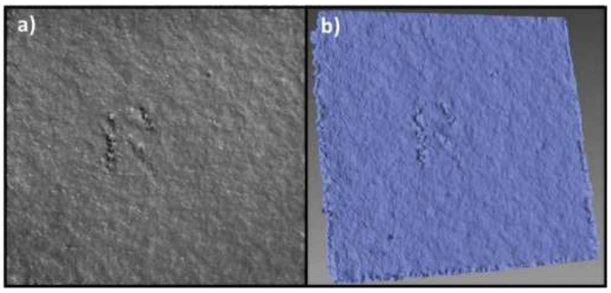
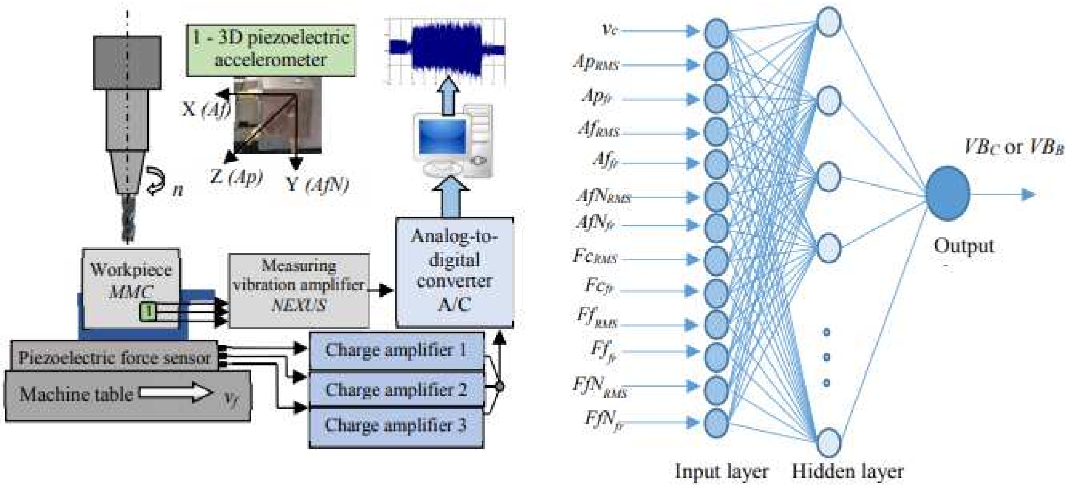


Figure 73. Real-time 3D surface measurement [145]. (a) Actual surface (hi-res image); (b) 3D scanned point cloud data.

3.5.7.6 2020

Wiciak-Pikuła et al. [164] employed neural networks to predict the wear of cutting tools during milling of aluminum matrix composites. MLPs were employed to associate the wear level of the tool with acceleration and cutting forces. This enables timely replacement of the tool in order to preserve the quality of the machining.



(a) (b)

Figure 74. Prediction of cutting tool wear level using ANNs; courtesy of [164]. (a) Conceptual description of the experimental setup. (b) Structure of the MLP.

Spruck et al. [165] employed deep neural networks the quality assurance of weld seams. Their system was actually a DNN-based classifier, for labeling images obtained by laser triangulation. Training of the systems required image assessment by experts. Upon training, classification accuracy was over 96%.

Franciosa et al. [101] employed digital twins targeting quality improvement. The benefits of their approach were (i) faster selection of process parameters; (ii) capability to automatically adjust process parameters by leveraging stochastic uncertainty; and, (iii) real-time closed-loop control with adaptive selection of new set of process parameters.

Kwon et al. [147] employed deep neural networks to analyze laser images and assess the quality of microstructure in metal sheets. The proposed model exhibited as hit rate over 98.9%. The authors attempted to fine-tune the architecture of the network and found that performance was elevated when the number of layer was increased while decreasing the number of nodes in each layer.

Meiners et al. [166] suggested a two-stage approach based on machine learning to optimize and automate the process control in batch production, accounting for including also changes in raw material and plant conditions, as well. The proposed configuration went beyond classic control systems by not relying on predefined rules and expert experience; instead, it was capable to extract interdependencies automatically from existent material, process and quality data.

Brito et al. [167] employed machine learning in a collaborative robotic environment for quality inspection. A robot was responsible for inspection and corrective action in the quality control system, supported by an intelligent system that could learn and adapt to the inspected parts. The underlying method was reinforcement learning.

San-Payo et al. [168] developed a classification model to be used in quality control using machine learning. The goal was to identify defective products using pictures taken from mobile devices. They employed an incremental learning algorithm that enabled learning new classes during the classification process. Features were extracted using convolutional neural networks.

One of the main defects in manufacturing printed circuits boards is the attachment of the silicon die on the substrate. In Dimitriou et al. [169], a diagnosis system was developed in order to estimate the volume of the deposited glue before and after the die attachment without human intervention. A laser scanning module was applied to obtain a point cloud of the PCB and the glue's volume prediction was achieved via the employment of several AI algorithms. The proposed method was validated in operational conditions without interfering with the manufacturing procedure.

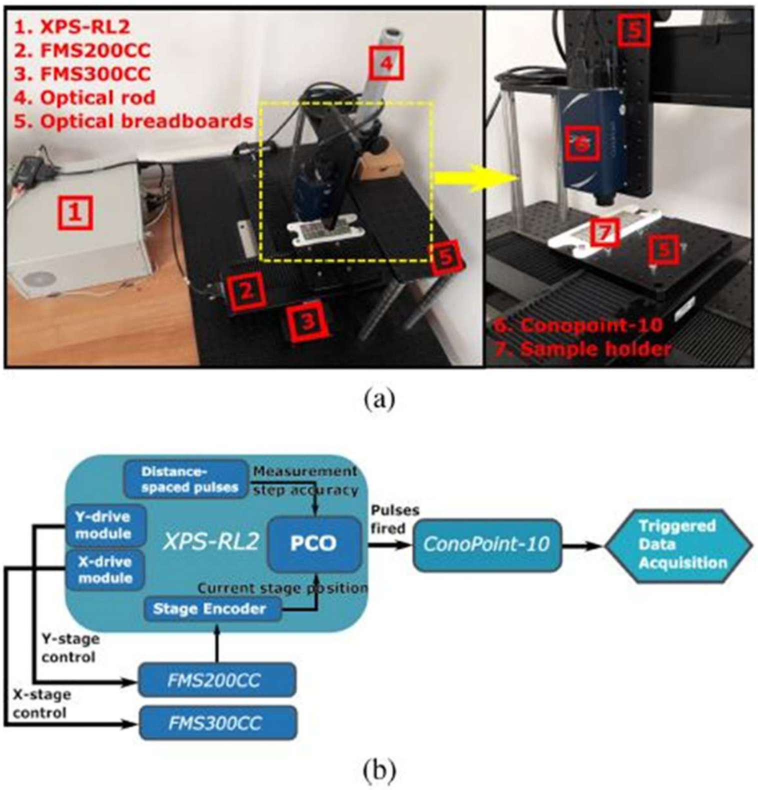


Figure 75. (a) Laser scanning module; (b) Operational flow of the scanning system [169].

3.5.8 AI algorithms for predictive maintenance

Predictive maintenance is strongly based on (1) monitoring and data gathering, and (2) decision making. Following this concept Tiddens et al. [170] reported the following approaches, focused on specific successful case studies:

1. **Experience-based maintenance** technique for steel manufacturing equipment.
2. **Reliability statistics** for aircraft tires.
3. **Stress-based maintenance** technique for a military transportation aircraft structure.
4. **Degradation-based maintenance** technique for rolling stock components.
5. **Physical model-based maintenance** technique for a military helicopter structural part.

3.5.8.1 2015

Bangalore and Tjernberg [171] introduced an ANN-based monitoring approach using nonlinear autoregressive neural network with exogenous input (NARX), to estimate the condition of gearbox bearings of wind turbines. This methodology used the Mahalanobis distance (MD) metric to detect the presence of an anomaly after the application of the trained ANN to estimate the average gearbox bearing temperature. The results demonstrated that the proposed ANN-based condition monitoring approach can offer effective predictive maintenance by indicating severe damage in the components.

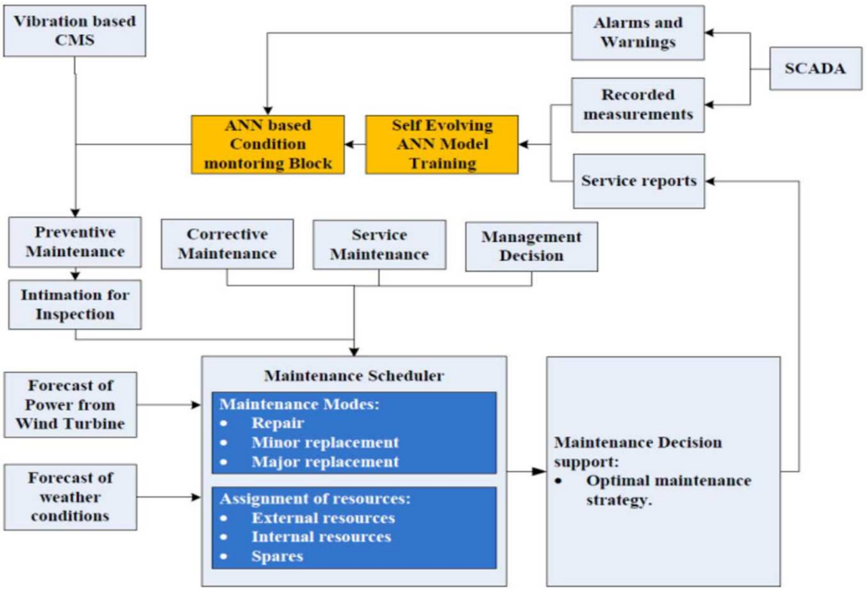


Figure 76. Proposed SEMS framework [171] .

Langone et al. [172] explored the application of the AI method of Least Squares Support Vector Machines (LS-SVMs) in effective early fault detection in modern industrial machines. Two different approaches were proposed for predictive maintenance in a use case study that regards a vertical form seal and fill (VFFS) machine. The first deploys kernel spectral clustering (KSC) for real-time machine condition monitoring, whereas the second approach utilizes a nonlinear auto-regressive model (NAR), to recognize dirt accumulation in the jaws. Based on the results produced, LS-SVM can successfully predict mechanical conditions based on sensor data, achieving at the same time higher performance than basic methods.

Abu-Samah et al. [173] presented a methodology based on Bayesian Networks for failure prediction, using event-driven contextual data as predictors. This approach explores the extraction of rules and patterns to forecast potential failure occurrences. This is a 4-step methodology where the first two steps regard the development of the Bayesian Network, that is, the identification of failure predictors and data pre-processing along with BN learning and optimization. The last two steps involve pattern extraction for all failures and the computation of the predictability index in terms of prediction accuracy, precision and lead time. This study offers promising results for prediction and can be extended by utilizing machine learning algorithms for rules extraction.

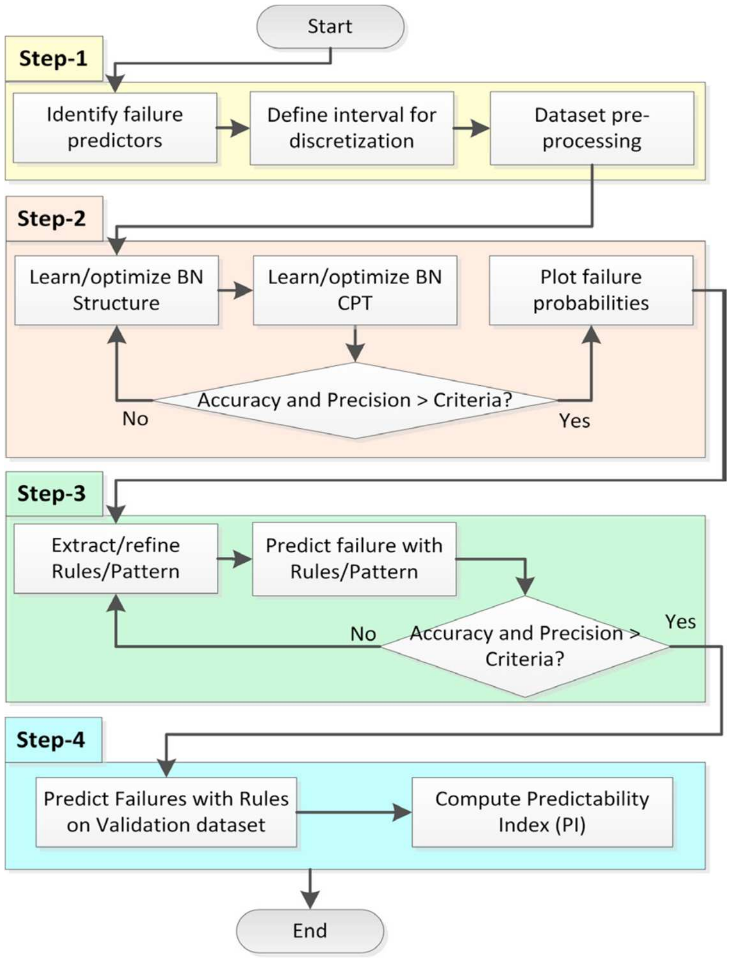


Figure 77. Methodology for failure detection before its occurrence [173].

Confalonieri et al. [174] developed a framework comprised of hardware, software and methodological interventions to design an innovative Decision Support System (DSS) for early identification of manufacturing problems. The data provided by sensors are processed by an ANN-based model which decides for preventive maintenance interventions. The proposed model consists of three main modules, responsible for data collection, status assessment, optimization and AI learning. The results produced demonstrate 95% of accuracy in preventively recognize an anomaly, further fostering a maintenance operation.

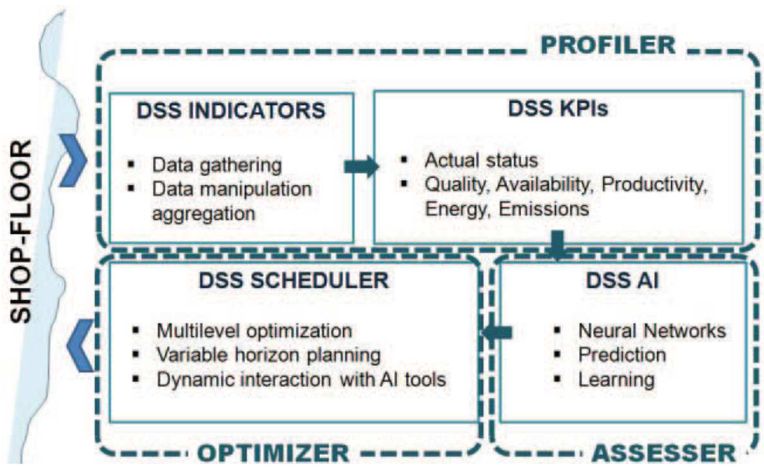


Figure 78. DSS high-level architecture and functionalities [174].

3.5.8.2 2016

Wu et al. [175] proposed a novel approach in the field of mechanical failure predictive maintenance, concerning machinery prognostics upon utilization of a cloud-based parallel machine learning algorithm. This study's main objective was to investigate the performance of the Random Forest (RF) algorithm and its parallel implementation, using the MapReduce framework. From the results, it emerged that the utilization of random forests produces very accurate predictions, while a notable speedup was demonstrated through the building of a large number of decision trees.

Krenek et al. [176] performed a review of ANNs and their applications in predictive maintenance and more specifically in the cases of electrical appliances early fault detection, mechanical damage and crack detection, detection of faults on pneumatic systems as well as robotic manipulator monitoring. The most common architecture utilized is the Multi-Layer Perceptron ANN (MLP-ANN) due to its simplicity, thus making it suitable for simple classification of faults. The results achieved by MLP design are 95%.

Another review study was conducted as well by Patwardhan et al. [177] regarding predictive maintenance through big data. The detection of anomalies in industry relies on large amount of real-time data in which data processing techniques are applied, fostering the application of preventive maintenance and the overall optimization of industrial processes.

Rødseth and Schjølberg [178] implemented a structured approach in the domain of predictive maintenance that is based on the Profit Loss Indicator (PLI) and this approach was applied in the manufacturing industry. Since maintenance has a significant contribution towards sustainable manufacturing, a key performance indicator such as PLI can help in this direction. In particular, it entails the ability to assess the status of the green aspect in manufacturing by calculating unintended time losses and waste, further improving availability and minimizing the operational costs.

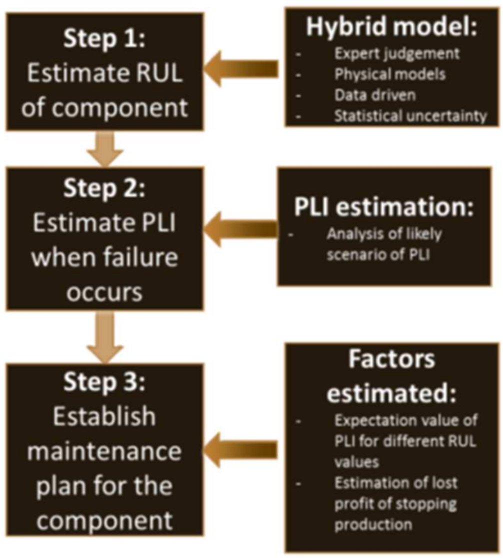


Figure 79. Structured approach for data driven predictive maintenance [178].

Ben Said et al. [179] pay attention to the Semiconductor Industry being one of the fastest growing and important manufacturing domains. They present a methodology which utilizes Bayesian Networks (BN) for making decisions about effective maintenance procedure over potential unscheduled breakdowns. Although the proposed BN-based model does not allow real-time monitoring, it is quite promising and supportive to expert's knowledge. With a 49% of gain in productive time from long failure durations, this methodology can help SI in improving production capacities.

Ali et al. [180] provided a review concerning the combination of an acoustic emission technique with AI methods as regards machinery condition monitoring and fault detection. Acoustic emission signals are used for gear and bearing condition monitoring and fault detection which is the main concern of this approach and its efficiency. For preventing machinery performance degradation, malfunction or catastrophic failures, certain reliable techniques for health condition monitoring and failure prognosis are required. AI methods which have been widely used for fault detection of machine tool were utilized in this approach. These AI techniques including ANN, SVM and genetic algorithms (GAs), were employed for proper fault diagnosis, classification and localization.

3.5.8.3 2017

Li et al. [181] suggested a framework for predictive maintenance within the scope of Industry 4.0. The proposed framework consisted of five discrete modules: sensor selection and data acquisition, data preprocessing, data mining, decision support, and maintenance implementation.

3.5.8.4 2018

Wang and Wang [182] identified a critical issue in predictive maintenance: the features fed into AI algorithms are typically selected manually, relying on the experience of process engineers who understand the physical and mechanical processes. Such an approach suffers from different kinds of bias and is very labor intensive. Moreover, the selected features are specific to a particular learning task, and cannot be easily reused in a different task. To overcome these disadvantages, they have developed a general framework for predictive maintenance based on deep learning (Figure 80). This framework targets automatic feature extraction from the raw data that are most suitable for solving a particular learning task; this can be very beneficial for predictive maintenance in terms of effort, cost and delay.

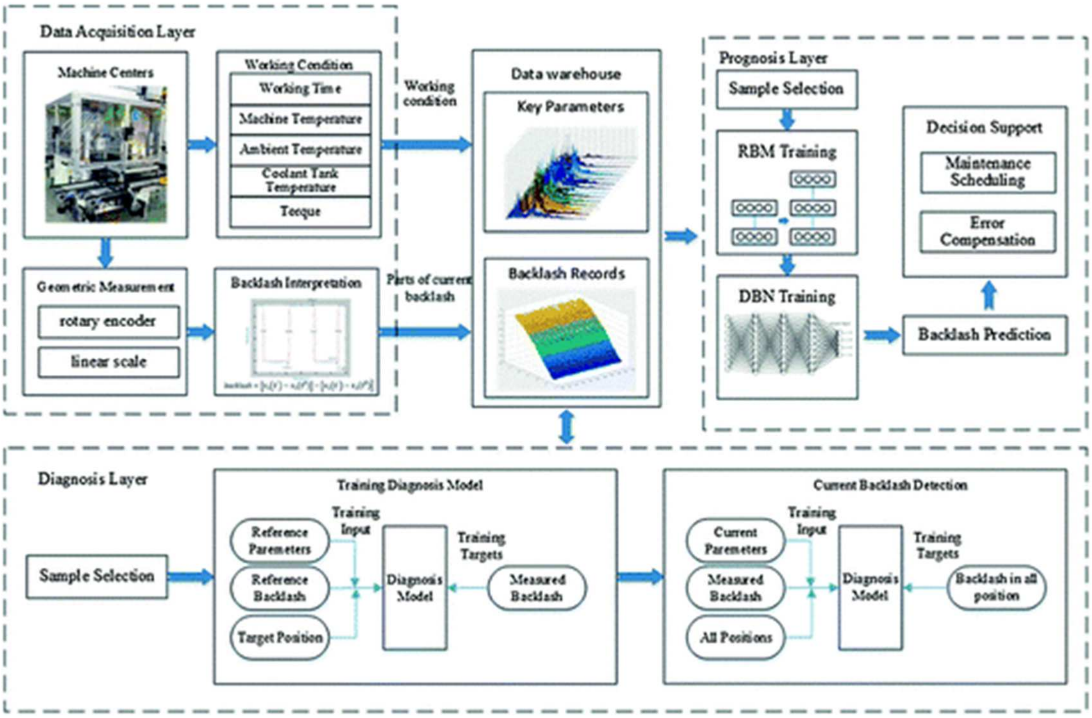


Figure 80. A framework of predictive maintenance based on deep learning [182].

3.5.8.5 2019

Cavalho et al. performed a systematic review of machine learning algorithms targeting predictive maintenance [3].

Chuang et al. [183] employed AI combined with edge devices and IoT to perform data-driven predictive maintenance; this framework is conceptually shown in Figure 81. The authors used an edge device (Raspberry Pi) to gather data from multiple distributed sensors, and process it and determine the health status of an experimental platform using deep learning. The developed technique was efficient and quite accurate; therefore, it is a good candidate for real-world applications.

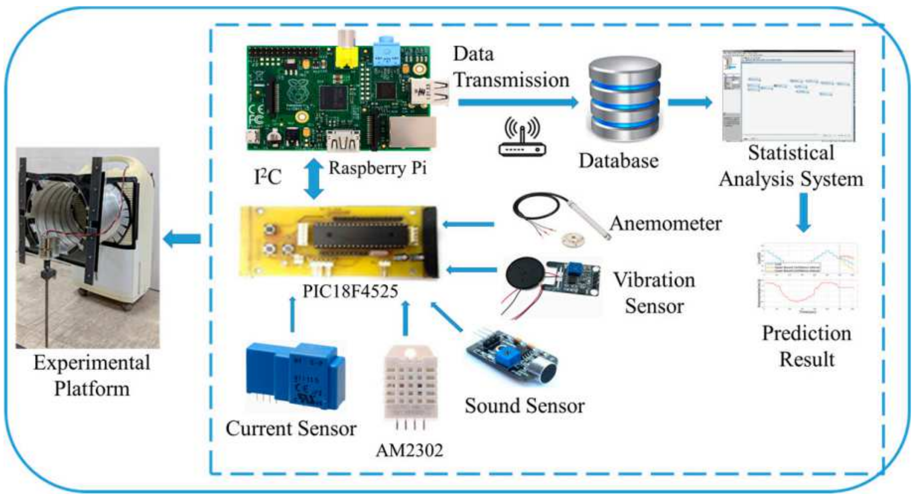


Figure 81. Overview of predictive maintenance framework, involving edge devices, IoT, and AI [183].

A method for predicting future failures of a motor using neural networks was developed in [184]. The experimental setup consisted of a cooling fan coupled with several magnets simulating typical motor vibrations. The measurements were conducted via an accelerometer in a laboratory environment and the introduced model showed that the employment of neural networks in performing predictive tasks looks promising.

Figure 82. Hardware setup for simulating vibration in motors [184].

Pinto and Cerquitelli [185] used artificial intelligence techniques like KNN, RT, CNN in order to develop a fault detection module that is able to predict the remaining life for industrial robots. The tuning of the model's parameters was achieved via the Grid Search algorithm. Furthermore, the methodology was validated on a real case scenario with Comau industrial robots and the outcomes were satisfied.

3.5.8.6 2020

Çınar et al. suggested deep learning for predictive maintenance within Industry 4.0 [186]. The authors explored various AI approaches, including artificial neural networks, support vector machine, decision tree, random forest, logistic regression, extreme gradient boosted trees, gradient boosted machines, linear regression, symbolic regression, etc.

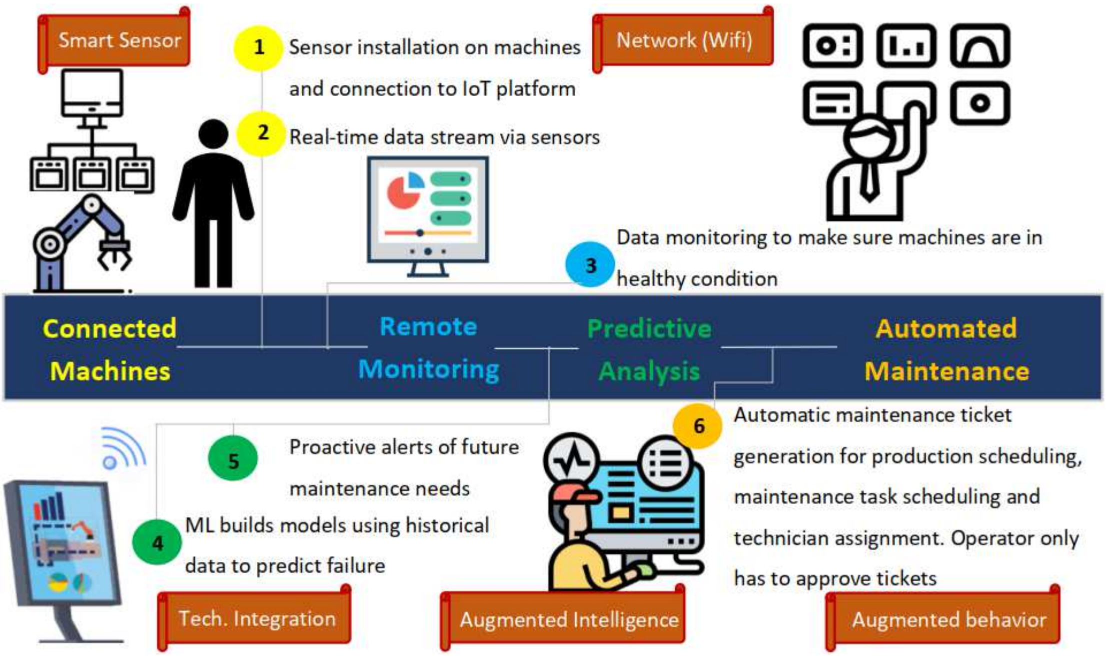


Figure 83. Framework for deep learning-based predictive maintenance [186].

Daniyan et al. raise the concept of a learning factory which involves the integration of academic learning environment into the shop maintenance floor of a railcar industry [187]. The predictive module employs AI, namely ANNs, to correlate temperature variations to the remaining useful life of a railcar (wheel-bearing health status).

3.5.9 AI for Zero-defect manufacturing

All previous concepts and technologies are envisioned to merge into unified frameworks towards zero-defect manufacturing. The SOA frameworks identified in the literature are listed in the following paragraphs.

Concerning zero-defect detection and monitoring, there are many and interesting applications and methodologies proposed to tackle the ongoing challenges in this field. The authors in [188] employed various configurations of deep convolutional networks and discuss how different parameter settings affected the accuracy of defect detection results. Additionally, the authors in [189] examined the problem of induction motor fault diagnosis utilizing a convolutional discriminative feature learning method. A back-propagation (BP)-based neural network was used to learn local filters capturing discriminative information and then, a feed-forward convolutional pooling architecture was built to extract final features through these local filters.

In [190], a convolutional neural network, based on LeNet-5, was proposed to extract the features of the converted 2-D images and eliminate the effect of handcrafted features in fault diagnosis. CNNs have been also applied for machine parameter prediction in industry, to attain best quality for a specific industrial product [191]. Tello et al. extended the previously proposed randomized general regression network (RGRN) model into a new deep-structured ML technique for defect detection and classification of diverse defect patterns providing a remarkable overall performance [192].

Moreover, the authors in [193] introduced a methodology based on hierarchical convolutional neural networks (HCNN) characterized by two main features: the fault pattern and fault severity. The classifiers in each level of the diagnosis network were trained in a single training stage. HCNN showed outstanding performance against traditional two-layer hierarchical fault diagnosis network and other machine learning techniques.

In another interesting case study, advanced CNNs found extended applicability in automatic fault diagnosis by estimating accurately the volume of glue deposits on Printed Circuit Boards (PCB) [169]. The proposed three-dimensional convolutional neural network (3D-CNN) architecture was called RNet and outperformed other deep learning approaches.

Another promising framework is presented in [194] where a deep learning method was implemented to achieve high performance on machine fault diagnosis. Transfer learning was incorporated in the training phase of the proposed DL architectures, producing an improved model training process, for the examined classification problem. Sensor data were used as input and were converted to images by conducting a wavelet transformation.

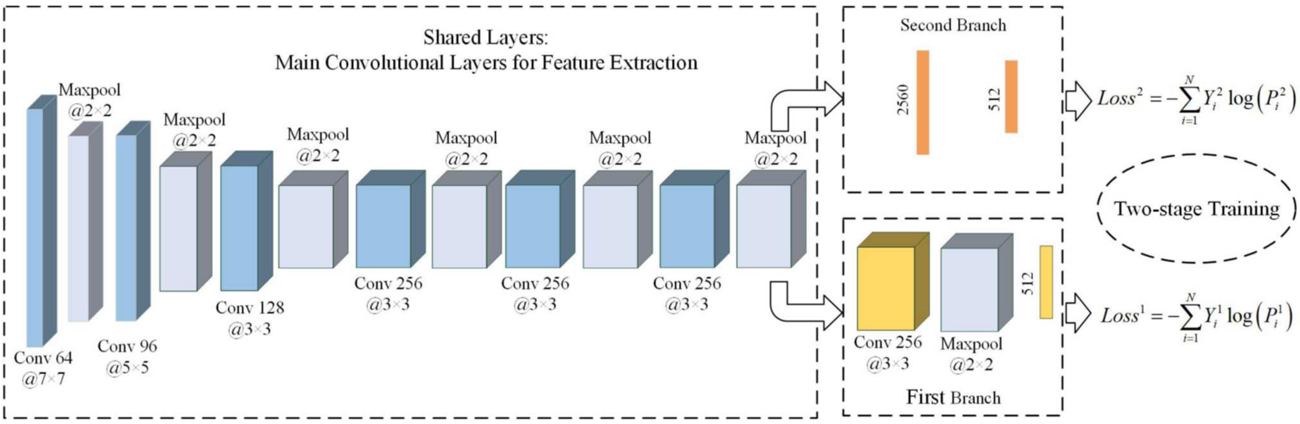


Figure 84. Structure of HCNN and its training method [193].

The study in [195] investigated a technique to minimize the number of defects during quality control procedures in a fluid dispensing system. The authors employed real time data acquisition to predict the formation of droplets as well as to estimate the failed products on an industrial experiment. The proposed methodology utilizes the Principle Component Analysis (PCA) in order to detect faults on the quantity of the dispended fluid.

While DL has certainly fostered progress in fault diagnosis of one-dimensional (1-D) and two-dimensional (2-D) signals, it has not found wide application in processing 3-D sensory from industrial shopfloors. Recently, Dimitriou et al. [196] developed a method where deep neural networks were employed to simulate changes in the 3D geometrical shapes of inspected parts in a batch taking into account previous measurements of the production. The geometric variations were modelled via 3D Convolutional Neural Networks, hence forthcoming actions leading to defects could be predicted. The validation of the proposed technique was established on a microelectronic use-case and the results showed that the suggested technique can efficiently predict defects during the manufacturing process.

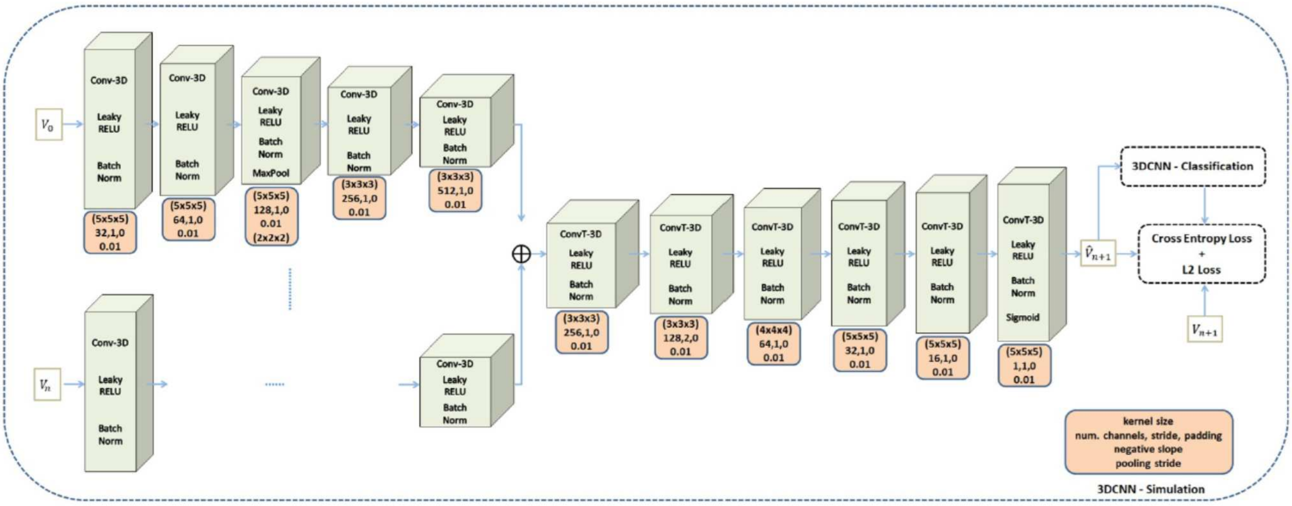


Figure 85. The 3D-CNN architecture of the simulation model [196].

The need for the development of a reliable quality control system that can lead tozero defect manufacturing process is urgent especially in pharmaceutical industry. Therefore, Dengler et al. [197] presented a system that is based on machine learning algorithms such as Decision Trees, SVM and CNN to identify multiple types of errors during the assembly procedure of medical products. The methodology was tested in two real use cases and the results exhibited that the proposed technique is capable of detecting all the defective products but also reduces the false rejections on a sufficient percentage.

3.5.10 Virtualization in smart manufacturing

The fourth industrial revolution (Industry 4.0) is well underway and represents a transformative practice in the way many industry verticals conduct their business. It is based on the abundant use of the Internet of Things (IoT) along with Cyber-Physical Systems (CPS) that are intertwined in the whole industrial process. Furthermore, the explosion of big data generated by these systems has entailed the evolvement of key technologies such as Artificial Intelligence, Computer Vision and Extended Reality, humans (i.e., workers) that seem to constitute a big potential for the factories performance. Research efforts for enhancing human performance in the shop floor are already in place coping to maintain competitiveness, especially considering the ever-increasing reliance on automation. Such efforts are paving the ground for a new paradigm shift that could steer the human-cyber-physical systems symbiosis towards a new industrial revolution. The combination of technologies such as Augmented Reality (AR) for providing computer-aided support with the rapid decision making provided by Artificial Intelligence (AI), as well as the advanced systems' perception and monitoring that can be achieved through the advances in Computer Vision (CV), act as a key enabler for putting the worker at the center of the loop, thus becoming an integral part of the smart manufacturing of tomorrow.

In combination with AI and IoT, AR proves to be a very substantial facet of the smart manufacturing process able to elevate the capabilities of workers and provide them with sufficient stimulation pertaining to a production issue, assisting them in resolving it and thus improving the adhering processes, even before they are carried out [198]. AR enables workers to advance up the skill-chain, leveraging on the timely delivery of contextual knowledge and information about carrying out a specific task, delivering a significant boost in workers' situational awareness and pointing to the potential for efficiency increase in almost all areas of industrial application [199]. The topics of assembly, maintenance, product design, training and learning, are the most common research fields where AR approaches have been suggested, while other topics such as safety, ergonomics or remote collaboration have recently emerged as new foci for research [200].

An illustrative example of how AR can facilitate useful guidance for products' assembly and prototyping in real environments is presented in [201]. The work discusses an AR-aided system that makes available to the users the option to select and combine different virtual product parts working in the real assembly environment, integrating product with workplace design and planning activities, to improve the efficiency and quality of both in assembly operations.

AR represents another key technological enabler entailed by relevant approaches in smart manufacturing, highlighting the necessity for the workers to keep their hands free, without needing to hold any type of displaying devices such as tablets, to be able to continue operating without any obstacles imposed. Such a hands-free approach is presented in [202] regarding a system for constraint analysis able to perceive and interpret the users' manual assembly of virtual components without the need for supporting CAD information. In this case, the users are able to use their hands for manipulating the parts as they would do at the shop floor.

AR also plays an important role in human-robot cooperation, which is mandatory in industrial spaces. Toward supporting human-robot interaction, [203] introduces an AR system that is able to monitor assembly / disassembly operations conducted by robots and allows the human operators to intervene when necessary (e.g., in the occurrence of errors), thus enabling the development of a cooperative and efficient assembly/disassembly strategy. Another aspect that AR facilitates safe and efficient cooperation of humans with robots in industry, is the assistance that can be provided through instructions and notifications. In [204] an AR solution is presented supporting workers by providing instructions and production notifications, in their field of view, while they are operating in cooperation with robotic machinery. Furthermore, as explained in [205,206], such systems can also reinforce the "safety feeling" of the workers who work close to large industrial machineries by visually alerting them when a potential hazardous situations might occur and preventing operations to be executed if they are dangerous for them.

Another field of application for AR in manufacturing is that of monitoring and timely indicating of potential defects that might occur in the production. Such a system is presented in [207], facilitating the monitoring of the manufacturing process of a product and the possibility for comparing it real-time with its CAD counterpart in order to identify potential defects. A similar approach that is detailed in [208] introduces a framework, based on the concept of Digital Twins, for providing data and information to the workers using AR, so as to perform efficient decision-making and higher level machine control. In such cases the system notifies the employee and provides them with visual cues pertaining to any identified flaws. Going one step further, the authors in [209] discuss a method that combines the capabilities provided by CV, AI and AR for monitoring the manufacturing production and thus assisting workers to productive maintenance. They rely their methods on well-established quality management methods (Lean, Total Productive Maintenance, and Overall Equipment Efficiency) and explore how they can be applied in an autonomous fashion with the use of the reported technologies. They have applied their method in a mass production process of a company and the first results were very optimistic since an important scrap reduction has been observed.

As already explained, the AR potential in the manufacturing process is well established, providing opportunities for leveraging several different aspects such as the configuration and maintenance of devices ([210,211]) machines and systems [212], the safety of the employees in the shop floor [213], the personalization of the products [214], training [215], and even worker motivation via gamification [216]. Of course, several aspects are still open and should be taken into account so that AR applications can be widely used in the manufacturing domain, such as improvements in accuracy, performance and price, the development of efficient and suitable UIs able to provide intuitive and non-blocking interaction of human with the machineries, as well as the existence of fast and stable internet-based collaborative infrastructures [198]. Furthermore, training the current industrial workforce in utilizing and accepting wearable AR technology as part of their everyday work is of paramount importance to facilitate wide-spread adoption, especially considering the unfamiliarity of workers with head-mounted technology due to a lack of hands-on experience with real-life tools [217].

In [218] the authors discuss a detailed taxonomy yielded by the way that AR is being deployed in smart manufacturing. They classify the studied works in four main categories, which pertain to the devices used for supporting AR, the manufacturing processes that the AR systems are deployed, the basic objective that the systems aim to address and the type of methodological approach that is followed to obtain the objectives. The big share of the manufacturing operations that the AR systems have been deployed appertains to maintenance, assembly and planning, while only a small percentage corresponds to training, monitoring and quality control. The observed low focus on quality control can be explained by the fact that so far this aspect has been faced under the rationale that it doesn’t depend on human decisions; instead, a machine-based decision process is considered adequate to address this need.

Today, this mentality regarding the employment of autonomous systems in everyday life has been totally reconsidered under the human-centered perspectives of reliability, safety and trustworthiness [219,220]. To that end, putting the human in the loop regarding the decision processes based on AI systems has started to become mainstream, not only because in this way the ethical concerns about autonomous system use are better addressed, but mainly because it seems that the human-machine symbiosis can generate superior results. A necessary modality for such an approach is the means of human-machine interaction, which can be facilitated using wearable AR technology. In this respect, manufacturing processes that have been so far relied on the decision-making efficiency of autonomous systems, such as quality control and zero defect, can now be subjected to a human-centric approach, involving employees operating at the shop floor able to instantly interact, in order to efficiently and timely resolve production problems. This concept is discussed in [221]. Specifically, a system for automatic defect detection of car body surfaces is introduced providing AR UIs to the employees through a Head-up Display (HUD), in order to interactively facilitate the quality control of the products. An AR based collaborative system connecting the worker with data originating from the industrial IOT and the suggestions from the AI, is illustrated in [222]. Through the system, human input in decision making is supported, as for example in troubleshooting activities in which is necessary to have information collected by the human to select the right procedure to execute. The different collaboration modalities that are provided for addressing these manufacturing operations include cases when the user should manually follow a sequence of predefined steps, or situations that entail the synergy of the employee with the system (e.g., machineries and analytics services), or finally cases that autonomous system actions should not be taken into consideration and the worker should take decisions on their own.

Today, the need for laying the foundations for the efficient human-machine symbiosis in smart manufacturing and especially in the domain of quality management and zero defect, is becoming imperative. Key enabler technologies for such an approach have already become mature enough, so as to aim at developing intelligent autonomous systems that actively cooperate with humans for the optimal decision making and effective production problem resolution. As already discussed, AR can constitute the means for facilitating this mutual relationship between the systems and human, in an intuitive and effective manner. In the context of OPTIMAI, opportunities for defect analysis visualization and interaction will be investigated. Using wearable HMDs, coupled with intelligent multimodal natural interaction, workers at the shop-floor will be able to actively address production defects, through an ecosystem that will ensure the seamless confluence of diverse computing platforms, unobtrusive monitoring and sensing (e.g., via computer vision), and producing advanced, immersive and tangible visual representations of defect information. Furthermore, OPTIMAI will focus on a context aware adaptive interaction framework, based on a customizable decision-making engine, to support personalized interaction with wearable AR solutions for increasing worker awareness in manufacturing scenarios.

4 Ethics in AI for industry

This chapter discusses AI ethics in the industry context. It is organized as follows: **Section "Overview of AI ethics in industry"** introduces a connection between AI ethics and industry, opportunities and challenges raised by AI, and provides a brief overview of ethical frameworks and guidelines relevant for industry and the OPTIMAI project. **Section "Facing the implementation of AI ethics in OPTIMAI"** focuses on the implementation of AI ethics in OPTIMAI, including monitoring strategies and actions. **Section "Responsible research and innovation in industry"** places AI ethics in a broader context of companies' responsibility towards society, corporate social responsibility (CSR) and responsible research and innovation (RRI). Last, **Section "Automation, digitalization, and meaningful work"** explores the relationship between companies as employers and employees, as their internal stakeholders, by diving into questions of automation, digitalisation, and meaningful work.

4.1 Overview of AI ethics in industry

The convergence between Web 4.0, Industry 4.0 and the Internet of Things (i) brings about new regulatory challenges for organisational data, responsibility, data protection, trade restrictions, agreements, standards, contract models, supervision, surety, monitoring and control, and (ii) tends to create and stabilise new regulatory (or socio-legal) ecosystems in a huge array of technologies adapted to the manufactures of a variety of new industry sectors, from automated vehicles to intelligent welding systems.

Lu [223] has pointed out that the integration of things, data, services and people—i.e. the convergence we are talking about—requires an enhanced interoperability (operational, systemic, technical and semantic) between: (i) Smart factories and manufacturing, (ii) smart products, (iii) smart buildings, (iv) smart homes, (v) smart facilities, (vi) smart transportation, (vii) smart grids, (viii) and smart cities. This is drawing the general interoperable informational space that the convergence between Industry 4.0, the Internet of Things (IoT) and the Web of Linked Data (WoLD) is creating in urban environments, everyday life, and in the workplace.

The potential benefits of AI for industry are abundant. PwC (2019) estimates that GDP could be up to 14% higher in 2030 as a result of AI, the equivalent of an additional $15.7 trillion, making it the biggest commercial opportunity in today's fast changing economy [224]. However, there are considerable ethical and legal challenges for the development and use of AI. Therefore, in recent years, public sector, research institutions and private companies have issued various principles and guidelines for ethical AI. A number of initiatives aimed to capture this proliferation and map the landscape of such frameworks. For instance, the EU-funded project SHERPA (*Shaping the Ethical Dimensions of Smart Information Systems: A European Perspective*) found over 70 relevant documents [225]. AlgorithmWatch AI Ethics Guidelines Global Inventory lists more than 80 documents, including industry related guidelines developed by Google, IBM and Microsoft [226]. The EU-funded SIENNA project (*Stakeholder-informed ethics for new technologies with high socio-economic and human rights impact*) provides an overview of international and national codes and guidelines with a particular focus on ethical guidelines by professional organisations, ethics advisory groups, and research ethics committees for Artificial Intelligence and Robotics (AI&R) [227]. While there is a multiplicity of such frameworks, codes and guidelines, it is worth mentioning a few particularly relevant for industry and the OPTIMAI project (Note: a comprehensive analysis of the ethical and legal framework for the OPTIMAI project is part of task T9.1 and deliverable D9.1).

The IEEE (Institute of Electrical and Electronics Engineers) Global Initiative on Ethics of Autonomous and Intelligent Systems, called 'Ethically Aligned Design' was officially launched in April 2016 as a collective program of the IEEE, the world's largest technical professional organization (IEEE, 2019) [228]. It identified over one hundred and twenty key issues, with several founding values and principles to be applied "to all types of autonomous and intelligent systems (A/IS), regardless of whether they are physical robots, such as care robots or driverless cars, or software systems, such as medical diagnosis systems, intelligent personal assistants, or algorithmic chat bots, in real, virtual, contextual, and mixed-reality environments" (IIIE 2019, 17): (i) Human Rights; (ii) Well-being; (iii) Data Agency; (iv) Effectiveness; (v) Transparency; (vi) Accountability; (vii) Awareness of misuse; and, (viii) Competence.

There are currently 14 approved IEEE Standards development activities in the IEEE P7000 Series, incorporating transparency, data access and control, algorithmic bias, robotic nudging, and well-being. Adamson and Chatila have offered a complete table of 52 IEEE ethical groups, practices, and trends [229]. These standards keep the difference between human consciousness and computer processing.

Other remarkable initiatives on Ethics are The Asilomar Principles for the *Future of Artificial Intelligence* [230], *The OnLife Manifesto* [231], the *Manifesto for conscientious design of hybrid online social systems*, and *Responsible Artificial Intelligence* [232]. Stemming from these works, we can point out several points that can be added to the IEEE principles to flesh them out, leading to the same direction: (i) The importance of explainability (or explicability) to steer clear of opaque decisions [233]; (ii) The emergence of machine ethics, or "how a machine could act ethically in an autonomous fashion" [234], and (iii) The development of bias-averse strategies to minimise negative impacts in society, avoiding the risks of harming vulnerable people.

In the context of OPTIMAI, we seek to apply commonly recognised principles and guidelines that are operational and directly useful in development practices. The work published by the High-Level Expert Group on Artificial Intelligence of the European Commission (AI HLEG), "Ethics Guidelines for Trustworthy AI" [235] will be followed. According to AI HLEG there are four high-level ethical principles: i) Human autonomy; ii) Prevention of harms; iii) Fairness; and, v) Explicability. These principles are turned into specific requirements for their practical implementation. These requirements are: i) Human agency and oversight; ii) Technical robustness and safety; iii) Privacy and data governance; iv) Transparency; v) Diversity, non-discrimination and fairness; vi) Environmental and societal well-being; and, vii) Accountability.

This ethics-based approach will be used to operationalize AI ethical principles into a specific context of application -*AI solutions in and for Industry*- which takes into account not only technological aspects of Industrial AI, but also other industrial requirements such as value creation, human-AI-interaction, ethical and regulatory aspects [236]. Moreover, such an ethics-based approach faces the challenges and limitations of a principled approach to AI Ethics (e.g., common aims and fiduciary duties, professional history and norms; proven methods to translate principles into practice, and robust legal and professional accountability mechanisms) as stressed by Brent Mittelstadt [237]. Therefore, we will derive from sets of guidelines for operationalisation of ethics by design for developers and for users of smart information created by the SHERPA project [238], and further developed by the SIENNA project [239]. Following these guidelines, we consider the responsible and ethical development of AI to be the outcome of three factors: (*i) Responsible development models and methods for the system;* (ii) *Responsible corporate structure and policy in AI and big data industry;* (iii) *Support for responsible development by society (e.g., by governmental institutions, educational institutions, professional organisations, clients)* [238].

The SHERPA project provides an effective strategy for and useful example of the operationalisation of ethical principles in both the design and use of AI and Big Data systems. SHERPA researchers translate ethical concerns into the existing software development and management processes in their Guidelines for the Ethical Development of AI and Big Data Systems: An Ethics by Design Approach, and Guidelines for the Ethical Use of AI and Big Data Systems.

For the design of AI and Big Data systems, SHERPA researchers analyse the Agile model, which is a dynamic one encouraging stakeholder collaboration, and note the process "…allows integration of changing demands from ethical requirements (e.g., relative to new functionality)." The Agile process consists of six phases including; Requirement Gathering; Planning & Designing; Development; Testing; and Evaluation.

SHERPA researchers also describe how to integrate ethical concerns into the CRISP-DM model, which consists of six phases which are sequential but can be iterative, including; Business Understanding; Data Understanding; Data Preparation; Modelling; Evaluation; and Deployment.

Similar to their approach of mapping ethical requirements into existing software development processes, in SHERPA's Guidelines for the Ethical Use of AI and Big Data Systems the researchers map ethical requirements onto management processes. Their example is COBIT, a five objective model for IT governance in organisations consisting of the following points that [240]:

1. jointly ensures that there is an overall governance framework for IT in place that aligns IT management strategy with overall corporate strategy and objectives;
2. ensures effective oversight of IT-related processes that ensures adequate and sufficient business and IT-related resources;
3. accounts for strategic risks;
4. ensures engagement of stakeholders, and
5. ensures that IT services are delivered efficiently and effectively

The requirements presented in this document ensure that ethical concerns are robustly incorporated or mainstreamed into the governance and management of technology in organisations with the appropriate roles, codes, programmes, and communication processes established to effectively accommodate the ethical use of AI and Big Data systems.

4.2 Facing the implementation of AI ethics in OPTIMAI

This section follows the AI ethical principles established by the High-Level Expert Group on Artificial Intelligence (AI HLEG) [241], which have been adapted to the context of OPTIMAI research activities from an action-guiding perspective. This approach allows us to glimpse which ethical challenges will be faced in OPTIMAI and also points out specific monitoring strategies and actions that will be implemented in order to put such AI ethical principles into practice.

4.2.1 Human autonomy

The principle of human autonomy implies that AI-enabled technologies should be designed and deployed in a way that respects and protects fundamental rights and ensures human agency and oversight.

AI-enabled technologies must ensure human dignity. In the workplace, the objectification and dehumanisation of employees should be avoided. Employees should be treated as self-determined subjects whose physical and mental health must be protected. Worker's dignity might also be undermined by the consequences that the deployment of AI systems in the workplace may have on the de-skilling of the labour force and the meaning of work.

Individual's freedom can be accomplished with mitigation measures against coercion, threats to mental health (e.g., pressure, stress) and surveillance. Ensuring genuine voluntariness is key. Given the power imbalance in the workplace, employees may feel coerced to use AI systems in the workplace or may fear detrimental consequences if they refuse to adopt them. The use of AI systems in the workplace may also lead to an advanced system of surveillance and monitoring to which employees may be subject [242]. Surveillance may cause "chilling effects" on employees and may also negatively impact their freedom, autonomy, and privacy. Therefore, legal (including human rights and privacy), social and ethical impact assessments must be conducted to strike the right balance between the intended benefits of the deployment of technology in the workplace and the possible negative consequences for employees' ethical values and fundamental rights [243].

To ensure human agency, employees should be able to make informed autonomous decisions regarding AI systems outcomes and have the skills to assess and challenge the system. Therefore, training sessions are encouraged to ensure that workers have the knowledge to understand how the system works and how to interact with it [244].

The purpose of human oversight is to prevent or minimise the potential risks of AI-enabled technologies. Meaningful human control can only be achieved if human-centric design principles and appropriate human-machine interfaces are embedded into the technologies. Additional measures should be implemented to ensure that users have the expertise, necessary competencies, and authority to exercise human control effectively, e.g., training sessions that enable the understanding of the capacity and limitations of the deployed technology, awareness of automation bias [245].

4.2.2 Prevention of harms

The principle of prevention of harms means that AI-enabled technologies should not cause harm nor have detrimental consequences for individuals. In the workplace, this implies that employees' dignity must be respected, and their mental and physical integrity protected. Particular emphasis must be placed on the potential harms that technology can cause or exacerbate to workers, who are considered by the HLEG vulnerable people given the power imbalance and information asymmetries with employers. To minimise the impact of AI-enabled technologies on workers, a participatory approach could be adopted where workers are involved in the development and deployment of the technology [246].

The potential harms that can be caused by AI-enabled technologies also require addressing: i) the technical robustness and safety of the technology; ii) privacy and data governance concerns; and iii) societal and environmental well-being.

Firstly, AI-enabled technologies must be robust, resilient, secure, safe, accurate, reliable and reproducible. Technical robustness and resilience should be ensured to prevent the exploitation of vulnerabilities by third parties and misuse [247]. Therefore, the existence of potential security risks must be evaluated at the design, development and deployment phases, and mitigation measures must be implemented in accordance with the magnitude and likelihood of the risks. Security and safety measures should also be put in place to enhance workers safety and prevent detrimental consequences. To this end, a fallback plan can serve to ensure safety in case of a system failure. AI-enabled technologies must also be accurate. Accuracy rates should be particularly high when such systems can directly affect individuals, as is the case with workers whose integrity may be compromised. Accuracy must be monitored on an ongoing basis and procedures to mitigate and correct potential risks must be implemented. Additionally, workers need to trust the system to use it, therefore reliability and reproducibility are key aspects to ensure the adoption of the technology among workers [248].

Secondly, the prevention of harms to privacy and data protection is paramount given the potential risks that AI-enabled technologies pose to these fundamental rights through the processing of massive amounts of personal data. These rights can also be at stake because personal information can be inferred from non-personal data [249]. Respect for workers' right to privacy and data protection must be ensured by complying with the GDPR and by aligning with existing standards or widely adopted protocols. Importantly, in IoT environments, it is particularly crucial to clarify data ownership, the roles of data controllers and processors and access to data [250]. Oversight mechanisms must also be put in place to ensure data quality (e.g. representativeness in the dataset) and integrity that minimises the risks of using biased, inaccurate or compromised datasets. Therefore, processes and datasets must be scrutinised and documented throughout the system's lifecycle. The ubiquity of IoT raises particular privacy concerns that require workers' genuine voluntariness which can only be ensured through stringent consent procedures and comprehensive and easily readable informed consent forms [248].

Lastly, the use of AI-enabled technologies should aim at benefitting society and the environment. AI systems must be designed, developed and deployed with sustainability and environmental friendliness in mind. Therefore, the ecological impact of the system should be evaluated throughout the system's lifecycle and measures to reduce such impact should be encouraged. The social impact of the system should be regularly assessed both at the individual and societal level. For instance, the evaluation of the impact of the technology on workers should cover physical and mental health issues, non-discrimination, de-skilling of the workforce, among others. As for the societal considerations, the impact on the job market and the societal consequences it may entail should be addressed [244].

4.2.3 Fairness

The principle of fairness entails equality, diversity and the prevention of discrimination and stigmatisation against individuals and groups. Fairness can be achieved by i) promoting diversity, inclusion and non-discrimination; ii) fostering societal and environmental well-being while reducing potential harms; and, iii) adopting accountability measures.

Firstly, diversity and non-discrimination can be enhanced with oversight processes that identify, examine, address and test biases in the datasets and at the design and development phases [251]. From a design perspective, technology should be understandable and accessible to all workers regardless of their age, abilities or characteristics. In this regard, the participation of relevant stakeholders with diverse backgrounds and viewpoints at the different stages is highly encouraged to ensure that diversity is embedded into the system [252]. In the workplace, for instance, impacted workers and their representatives can be engaged in such discussions.

Secondly, as pointed out above, AI-enabled technologies should be designed to strive for social and environmental well-being. Concerning the principle of fairness, the social impact of the system on workers should be evaluated in terms of causing or exacerbating discrimination, stigmatisation or marginalisation.

Lastly, accountability requires the implementation of appropriate technical and organisational measures to report the system's performance and provide effective remedy and redress to the extent possible. Such measures include the assessment of design processes, the underlying technology and the data sets used, which allows for the auditability of the system. Auditability involves reporting the negative impacts of the system, identifying appropriate mitigation measures and feeding them into the system [243]. These negative impacts can be identified and assessed through comprehensive impact assessments that must be conducted regularly [253]. Accountability also includes providing explanations of the system's outcomes and the ability to seek redress. To this end, internal communication channels can be established for workers to submit their complaints, without risk of retaliation, and seek redress for harms caused by AI systems [252].

4.2.4 Explicability

The principle of explicability requires transparency of the system – including the datasets, the inner workings of the system and the business model – which ultimately enables human oversight [243]. For systems to be transparent, traceability measures must be implemented.

This implies that datasets and the technology that underlies the system should be documented, e.g. the methods used for designing and developing the system, the methods used to test and validate it and the outcomes of the system. Given that traceability allows for the identification of the reasons behind systems' outcomes, it enables explainability. Explainability means the ability to explain the outcomes made by the system intelligibly [247]. To this end, the rationale behind a system's outcome should be understood and traced by humans. Crucially, Ifeoma Ajunwa (2021) argues that lack of transparency and explainability subjugate workers and deprive them of justice [254]. Therefore, if a system's outcomes cause harm to workers, explanations of how the system arrived at it should be provided to the worker in plain language. In this regard, communication is crucial since workers must be aware that they are interacting with an AI system in the first place in order to be able to request an explanation. Consequently, workers must be informed in a clear and understandable manner about their interaction with an AI system, how the system works and its purpose, as well as its capabilities and limitations [244].

4.3 Responsible research and innovation in industry

It is crucial to emphasise that AI ethics in the industry context is related to broader concepts of corporate social responsibility (CSR), business ethics and responsible business conduct (RBC), whereby companies integrate social, environmental, ethical, consumer and human rights concerns into their business strategy and operations and in their interaction with stakeholders [255]. In other words, it is "the responsibility of enterprises for their impacts on society" [256]. CSR tools include hard law and soft law instruments. Hard law involves binding legal instruments, such as those related to human rights: Universal Declaration on Human Rights, Charter of Fundamental Rights of the European Union and the European Convention on Human Rights. Soft law instruments have mainly a voluntary and self-regulatory character and include standards, principles, codes of conduct, and reporting initiatives to provide quantitative data on non-financial (societal and environmental) responsibility performances [257]. Soft law instruments involve, for instance: ISO 26000 Guidance Standard on Social Responsibility (ISO 26000); Social Accountability 8000 (focusing on workers' rights and workplace conditions); OHSAS 18001 (regarding the health and safety of employees and minimising the risk of accidents); ISO 14001 and Eco-Management and Audit Scheme (EMAS) [258].

Furthermore, AI-enabled technologies developed by industry are results of their research and innovation (R&I) activities. Therefore, responsibility of industry relates to a specific type of business strategy and operations, namely companies' R&I processes and outcomes. Responsibility in the context of R&I is known as the concept of responsible research and innovation (RRI), which focuses on the development of products and processes that are ethically acceptable, socially desirable and respond to the needs and expectations of people and the society [259]. According to the most well-known definition of RRI, developed by René von Schomberg, RRI is "a transparent, interactive process by which societal actors and innovators become mutually responsive to each other with a view to the (ethical) acceptability, sustainability and societal desirability of the innovation process and its marketable products (in order to allow a proper embedding of scientific and technological advances in our society)" . RRI emphasises the importance of the stakeholders' role in the R&I process, thus RRI "should be understood as a strategy of stakeholders to become mutually responsive to each other, anticipating research and innovation outcomes aimed at the "grand challenges" of our time, for which they share responsibility". Values and principles of RRI are relevant for AI ethics and include: (i) inclusion (also called engagement or involvement of society), (ii) anticipation (assessment at an early stage in research and innovation (R&I) of benefits and risks), (iii) reflexivity (reflecting on values and beliefs during R&I) and (iv) responsiveness (the ability to change routines, structures and systems to adapt to changing circumstances and new insights) [260].

Various other concepts and approaches incorporate responsibility into R&I processes and outcomes, such as social design, socially responsible design (SRD), eco- design, design for values, open innovation, social innovation, environmental innovation, sustainable innovation [261]. While there are differences between how responsibility is conceptualised and defined in these approaches, responsibility of industry for their R&I activities may serve as an umbrella term involving sustainability, societal, ethical, human rights, and environmental impacts.

4.4 Automation, digitalization, and meaningful work

Following from the foregoing overviews of the state of the art in AI ethics and responsible research and innovation in industry, it is instructive to consider an emerging issue with relevance to the relationship between employers and workers. This issue illustrates the necessity of careful and deliberate application and operationalisation of ethical principles and requirements, and ultimately corporate social responsibility—meaningful work in workplaces that are altered by new automated and digital technologies.

The concept of meaningful work, and what it entails in practice, has been the source of multidisciplinary inquiry for many years [262–264]. More recently, scholarship has been emerging relating to digital and automation technologies and how they might help or hinder meaningful work or moral development. As OPTIMAI technologies will be implemented and deployed in industrial working environments and will have implications for workers' experiences of meaning in the workplace as a result of the changing nature of tasks and how they are executed, it is worthwhile to consider this emerging literature.

Meaningful work, from an ethical perspective, can be conceptualised differently depending on the ethical framework consulted. Norman E. Bowie, from a Kantian deontological perspective, defines six criteria of what is entailed by meaningful work:

1. Meaningful work is work that is freely entered.
2. Meaningful work allows the worker to exercise her autonomy and independence.
3. Meaningful work enables the worker to develop her rational capacities.
4. Meaningful work provides a wage sufficient for physical welfare.
5. Meaningful work supports the moral development of employees.
6. Meaningful work is not paternalistic in the sense of interfering with the worker's conception of how she wishes to obtain happiness [262].

From a virtue ethics perspective, extrapolating from the work of renowned virtue ethicist Alasdair MacIntyre, Ron Beadle and Kelvin Knight argue that meaning "…supervenes upon the active and intentional pursuit of goods internal to practices…" and further "[n]ot only skills, maxims and rules but also practical judgment and moral character are learned through work that actualizes the good of a certain kind of life." [263].

Nevertheless, there is broad agreement that work is meaningful whereby it is purposeful and provides some autonomy and capacity for growth and self-development to workers.

Jilles Smids, Sven Nyholm, and Hannah Berkers provide a thorough account of the opportunities and threats to meaningful work by robots in the workplace (though their analysis can be read as applicable to many different technology driven workplace innovations) [265]. The authors identify five pathways to or sources of meaningful work including:

1. Pursuing a purpose
2. Social relationships
3. Exercising skills and self-development
4. Self-esteem and recognition
5. Autonomy [265]

The authors analyse the threats and opportunities arising for these five categories. It is instructive to provide an overview of each of these categories with reference to the literature emerging on the broad topic of digital and automation innovation in the workplace.

Pursuing a Purpose: Smids et al. argue that automation of challenging tasks can reduce workers feelings of purpose (they provide the example of how a doctor may feel less purpose where machine learning algorithms perform diagnoses) [265].

On the other hand, if technologies such as AI or robots assist in rather than assume tasks, or assume boring tasks, human workers may not necessarily feel diminished purpose or may be able to focus greater effort on more meaningful tasks [265].

Social Relationships: The replacement of humans with robots (or other automated or digital technologies for that matter) can plausibly lead to less social interactions between workers, increasing isolation and feelings of meaninglessness [265].

However, the supplementation or replacement of certain kinds of roles can also free workers' time so that it can be put towards other socially oriented [265]. In other cases, new technologies like internet of things may facilitate more collaboration between people [244].

Exercising Skills and Self-Development: The substitution of tasks by different IT artefacts may cause human skills to become obsolete, and "[t]he development and exercise of these skills then will no longer be a source of meaningfulness for human workers, and their job will be less conducive to self-realization." [265]. Shannon Vallor also warns that ICTs can result in moral de-skilling, which is to say the replacement of tasks by automated or digital technologies can reduce opportunities for practising skills that ultimately contribute to the development of practical wisdom and moral habituation and thus virtue [266].

Michele Loi argues that far from being enhancing, new technologies may disenhance more people (that is, reduce their abilities) than they enhance and contribute to job polarization [267].

On the other hand, technological innovation in the workplace may necessitate upskilling [265]. In manufacturing in particular, monitoring and machine-control tasks may require workers to upskill [268]. The use of wearables and AR/VR in particular lends itself to fast and efficient training [268].

Robots and Self-Esteem and Recognition: If human tasks are assumed by automated or digital technologies, human operators may feel less self-worth and their jobs may receive less social-recognition [233,265]. Michele Loi argues that a job may lose its prestige where machines do it better [267].

However, it may also be that job roles requiring adaptation and upskilling by human workers gain more prestige and recognition [265]. On this note, however, it must also be considered that new high value jobs may not necessarily be performed by the same workers precisely because of the higher skill requirements entailed [268].

Autonomy: Autonomy has already been discussed in some detail, however reviewing this value from the perspective of meaningful work yields additional insights worth considering during the development of technologies that alter the workplace and how workers experience it.

Very strict protocols relating to the use of new technologies may reduce the scope for workers' job crafting. Additionally, data driven innovations may lead to worker monitoring (including performance monitoring) which can undermine worker autonomy [265]. Wearables, for example, can monitor location, movement and sentiment [269]. VR/AR may also, for example, cause a shift towards task driven work with less autonomy (though there are trade-offs, see below) [268].

The opacity of machine learning algorithms may also reduce workers' understanding of their job, and thus autonomy [265].

On the other hand, the supervision and use of automated or digital technologies may increase worker responsibility and autonomy—enhanced agency may help workers better realise their goals [265]. Worker monitoring may also be for positive reasons, including health and safety [269], that can ultimately increase worker agency. According to Eurofound, "[t]he demand for skills when using wearable devices indicates a need for digitally educated workers who can work with data flows from wearables but also to monitor their own performance or interact with machines" [268]—therefore digital technologies can extend human agency.

5 Summary – Discussion of Results

This section provides a detailed summary of the conducted literature review analysis followed by a thorough discussion on the contribution of AI-based technologies in smart manufacturing. The most widespread AI technologies which were mined in this report are CNNs, DL, ANNs, etc.

These AI methodologies were employed in each one of the investigated domains, namely Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision and Augmented Reality, Quality Control, Predictive Maintenance and Zero-Defect Manufacturing.

5.1 Technical aspects of AI use in smart manufacturing

5.1.1 AI-enhanced metrology

The distribution of AI-technologies employed in smart metrology is summarized and visualized in Figure 86.

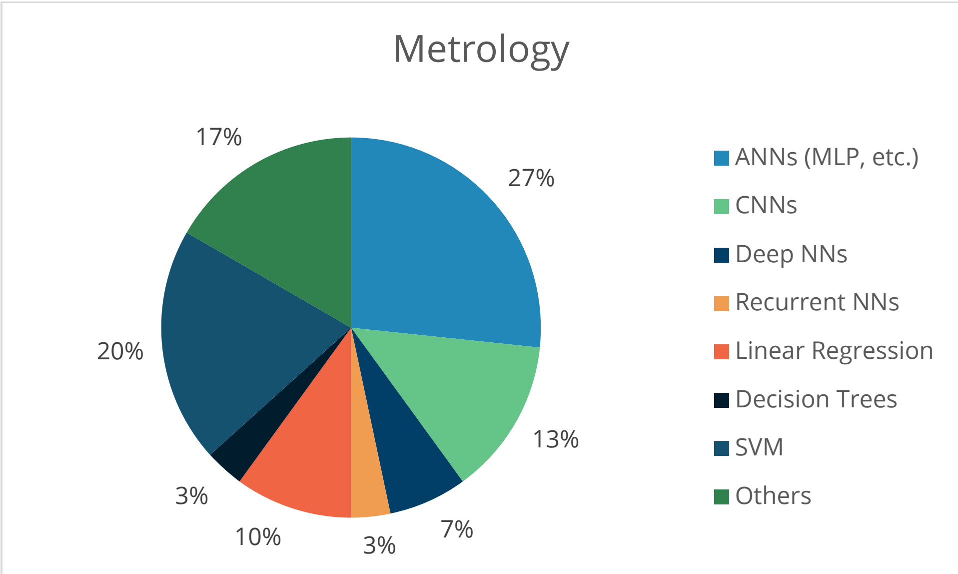


Figure 86. Distribution of employed technologies for AI-enhanced metrology.

It emerges that ANNs (27%), SVMs (20%) and CNNs (13%) are the dominant technologies in this field. Other machine learning methods (such as evolutionary computation, particle swarms, PCA, etc.) seem to have a notable presence in this domain.

5.1.2 AI-enhanced digital twins

The distribution of AI-technologies employed in AI-enhanced digital twins is summarized and visualized in Figure 87. As for the Digital Twins domain, there is a distribution supremacy of CNNs (28%) and Deep NNs (27%) against other ML based methods, such as genetic algorithms, particle swarm optimization (PSO) and Bayesian Networks. The learning capacity of CNNs and Deep NNs has brought them into a dominant position, being employed in roughly half of the case studies.

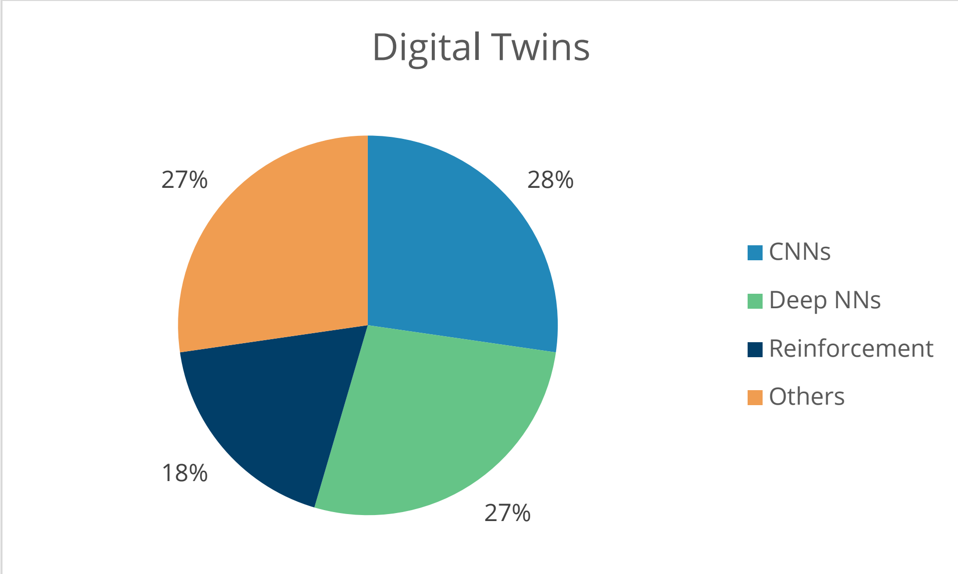


Figure 87. Distribution of employed technologies for AI-enhanced digital twins.

5.1.3 AI-enhanced IoT

Regarding AI-enhanced IoT, few research works (5 articles) were extracted and included in this literature review. Out of 5 articles, 2 utilize Deep NNs (40%), and each of the rest deploy ANNs, Reinforcement learning and knowledge-based algorithms (Figure 88).

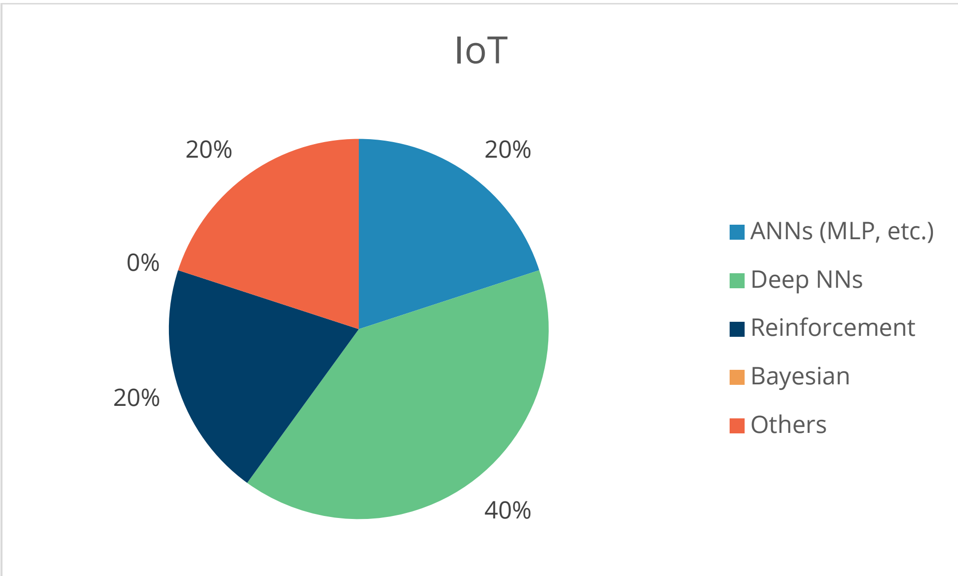


Figure 88. Distribution of employed technologies for AI-enhanced IoT.

5.1.4 AI-enhanced computer vision

In Computer vision, CNNs are the most commonly used methods to interpret and understand the visual world (Figure 89). Using digital images from cameras and videos, CNNs (44%), SVMs (26%) and deep learning models (18%) can accurately perform object detection, recognition and classification.

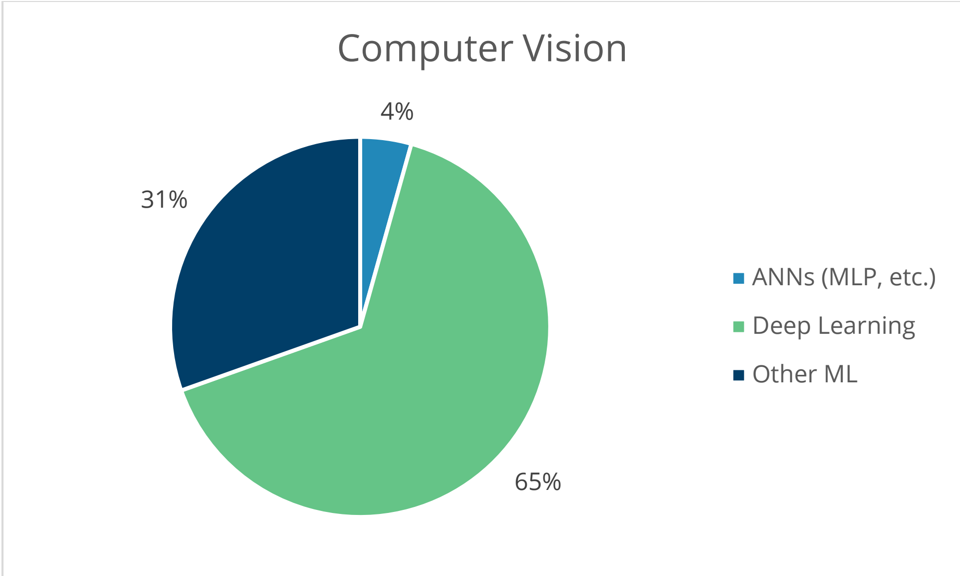


Figure 89. Distribution of employed technologies for AI-enhanced computer vision.

5.1.5 AI-enhanced augmented reality

The purpose of augmented reality is to visualize data without extracting patterns and proceed to further recognition, thus the use of AI techniques is not a priority which explains the limited number of articles in this domain. In this context, Deep NNs (57%) hold the biggest percentage whereas the other two (CNNs and Reinforcement learning) occupy the rest of the distribution, 29% and 14% correspondingly (Figure 90).

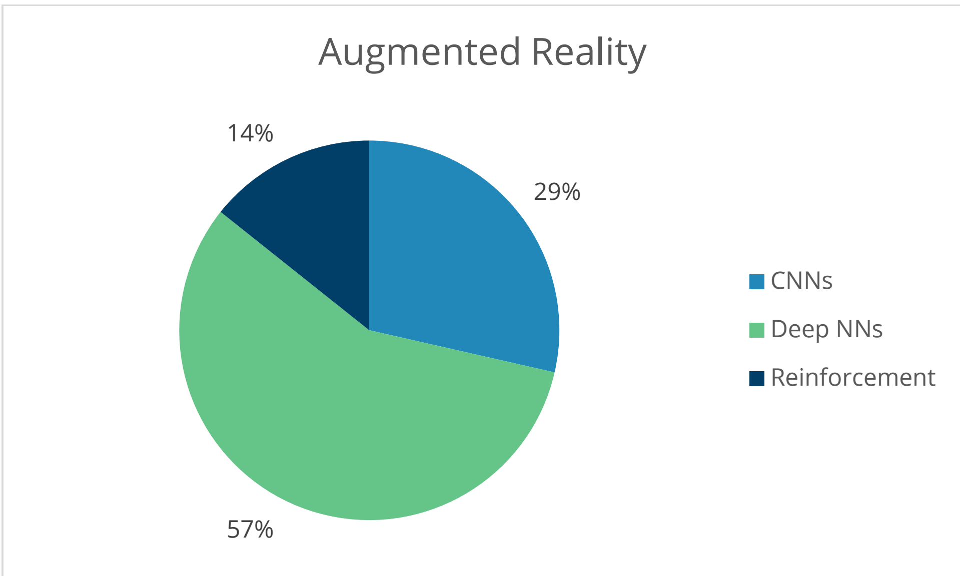


Figure 90. Distribution of employed technologies for AI-enhanced augmented reality.

5.1.6 AI-enhanced quality control

Regarding quality control procedures, CNNs are again the choice of preference (44%), along with SVMs (25%), as shown in Figure 91. In quality control operations, the preference of the individual AI-technology seems to be more scattered compared to the previously-mentioned tasks. This could be attributed to the fact that quality control is a complex task that requires more sophisticated algorithms, therefore, multiple AI-technologies are continuously assessed. Here, it is worth mentioning that only one article is found for each one of the AI categories (Deep NNs, Recurrent NNs, DTs, SVMs), and in AI category "others" the only article is devoted to the employment of interval Type II fuzzy logic in manufacturing quality assessment procedure.

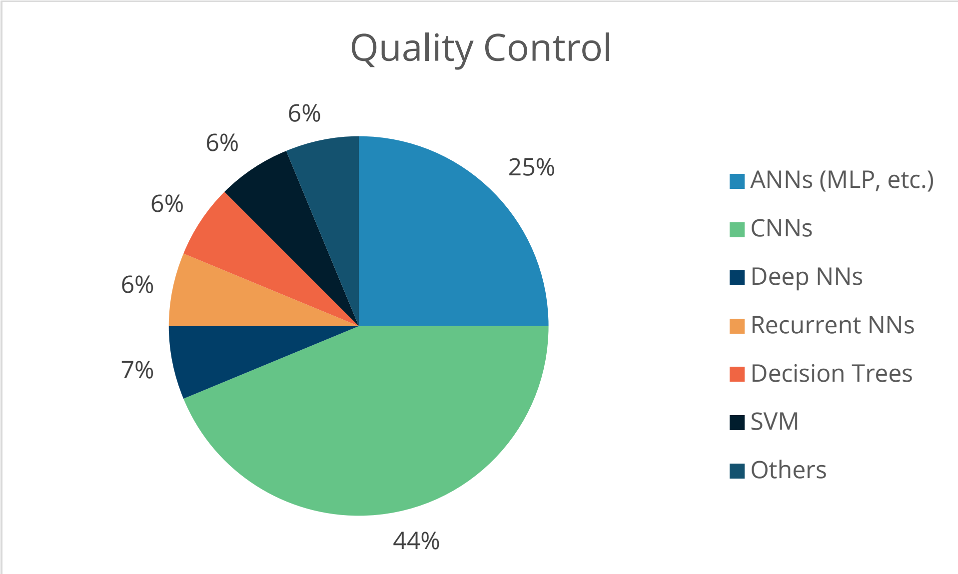


Figure 91. Distribution of employed technologies for AI-enhanced quality control.

5.1.7 AI-enhanced predictive maintenance

ANNs and Deep NNs are also very popular among predictive maintenance applications, as well. Their learning capacity has brought them into a dominant position, being employed in more than half of the case studies (Figure 92). ANN usage (37%) is followed by Deep NNs (21%) and SVMs and Bayesian Networks at smaller utilization ratios (11% respectively).

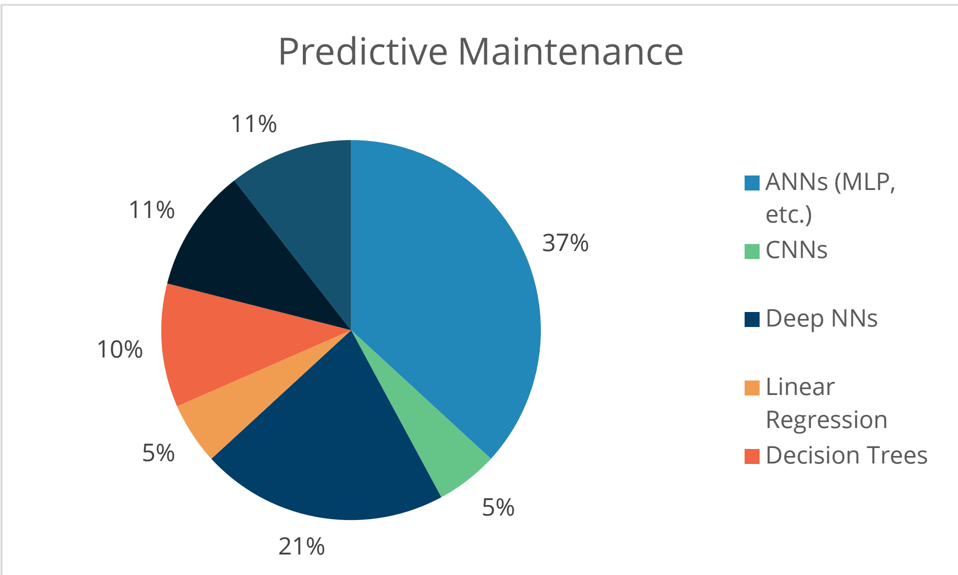


Figure 92. Distribution of employed technologies for AI-enhanced predictive maintenance.

Additionally, a recent article concerning a systematic literature review of machine learning methods applied to predictive maintenance [3] was scrutinised covering the main published solutions of predictive maintenance techniques based on ML methods.

5.1.8 AI-enhanced zero-defect manufacturing

Figure 93 represents the significant distribution of CNNs in ZDM compared to other state of the art ML techniques, as their architectures are able to deal with big multimodal datasets, addressing the problems of defect detection and fault diagnosis. CNN extreme usage (75%) is followed by smaller utilization ratios of SVMs, Decision Trees and other ML methods (e.g. PCA).

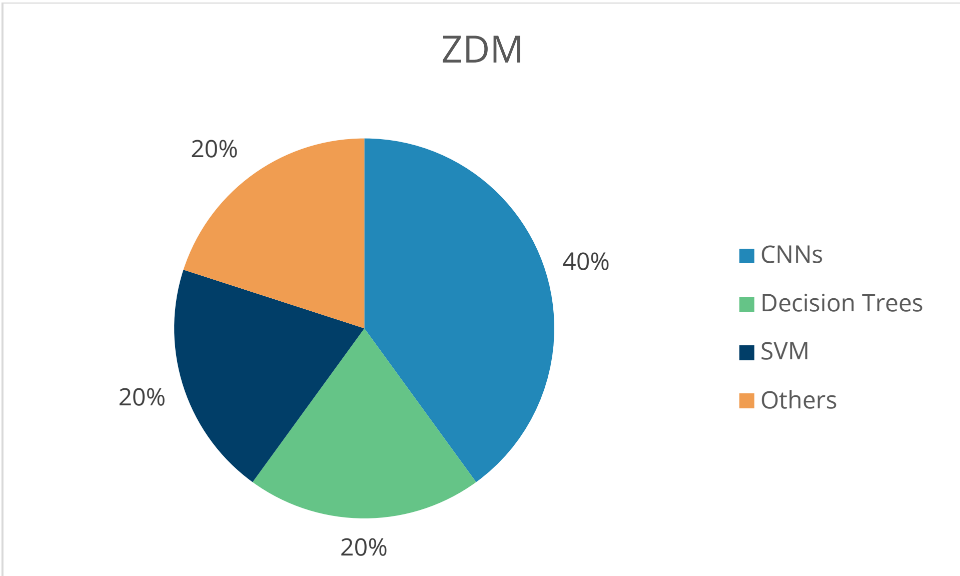


Figure 93. Distribution of employed technologies for AI-enhanced ZDM.

5.1.9 Distribution of AI-technologies in smart manufacturing

It is evident that ANNs and Deep Learning possess a dominant ratio in most – if not all aspects – of smart manufacturing. It is interesting to review a summary for the exploitation of the most popular reported AI-technologies in the various field areas.

An overall summary of AI technologies in all investigated fields in smart manufacturing is provided in Figure 94. It is obvious that CNNs, followed by ANNs and Deep NNs, have been exploited and applied to a greater extent than other popular AI methods. This is attributed to the fact that CNNs are among the most powerful deep learning techniques presenting notable capabilities on analyzing and classifying images, detecting objects, identifying defects, diagnosing faults etc. which improve the efficiency and performance of industrial processes.

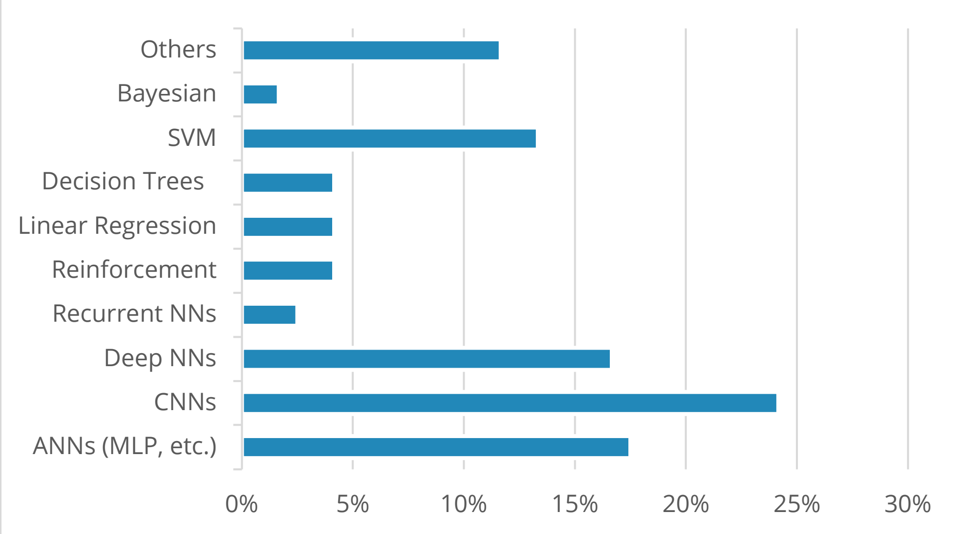


Figure 94. Overall summary of AI technologies in all investigated fields in smart manufacturing.

Furthermore, the category "Others" devoted to other ML methods such as fuzzy logic, genetic algorithms, evolutionary algorithms, PCA, has a significant share in various stages of smart manufacturing.

Taking one step further, we analyze the contribution of each one popular AI technologies to every field investigated in the realm of smart manufacturing (Figure 95 and Figure 96). It is clearly observed that CNNs are involved in all investigated fields except IoT with the biggest applicability. ANNs and Deep NNs show a similar trend with a smaller degree of participation in each category. The rest of the methods are involved in either 3, 4 or 5 domains with a moderate overall contribution.

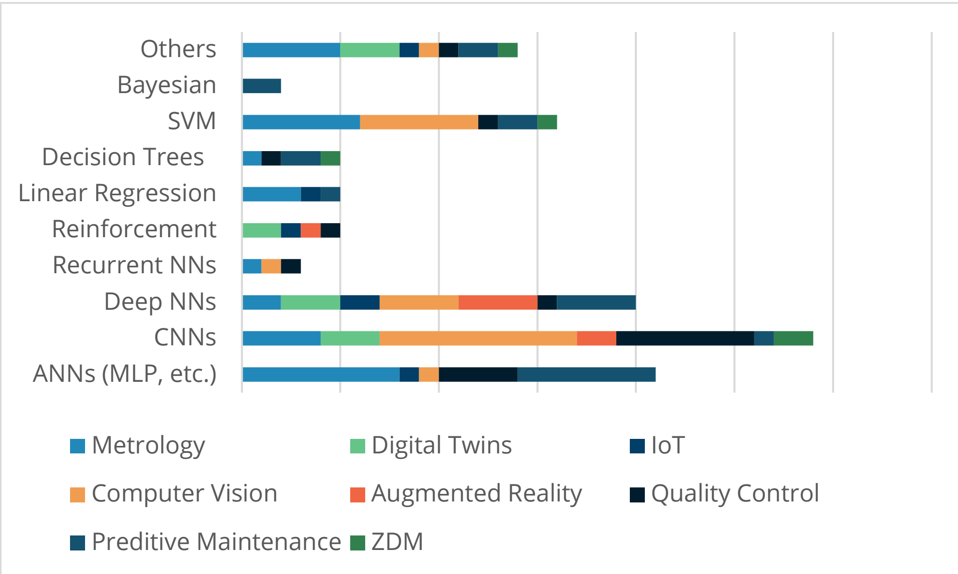


Figure 95. Use of most popular AI-technologies in various stages of smart manufacturing.

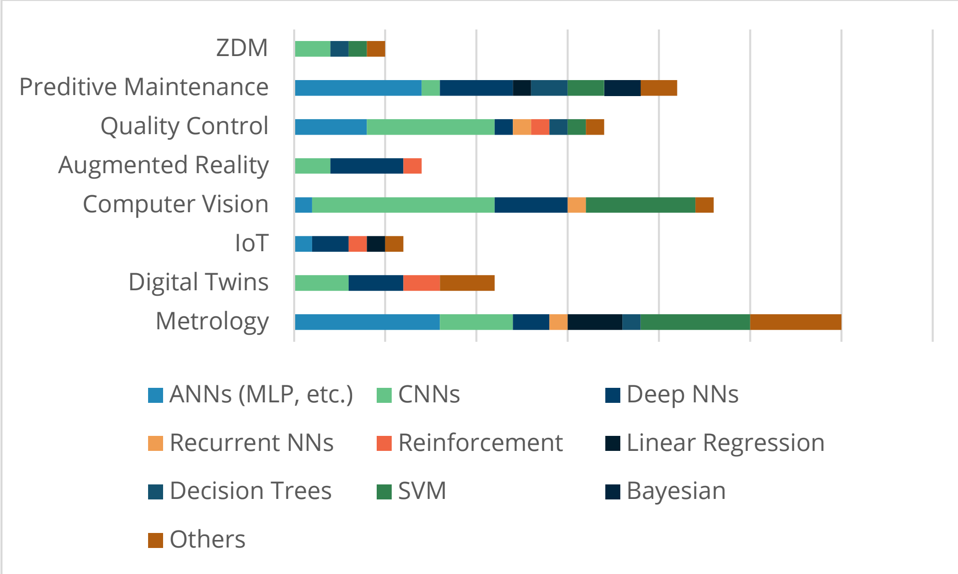


Figure 96. Dependence of smart manufacturing on most popular AI-technologies.

It is observed that ZDM, Quality Control and Computer vision are the fields with the highest involvement of CNNs, whereas Predictive Maintenance and Metrology encapsulate ANNs in a significant degree. We observe that Metrology is more mature than the other domains, as it uses almost all AI potentials; Predictive Maintenance and Quality Control are the next domains with the most AI methods applied in. Predictive Maintenance and ZDM are considered promising fields of intensive research, attracting the interest of research community on the efficient capabilities of deep learning. Hence, they establish the disciplines of Maintenance 4.0 and Smart Industry and provide opportunities for the development of new advanced AI and ML methodologies.

5.2 Ethical aspects of AI use in smart manufacturing

The reviewed literature demonstrates difficult regulatory challenges ahead stemming from the convergence of Web 4.0, Industry 4.0, and IoT technologies whilst also indicating new opportunities for new regulatory eco-systems. The foregoing has demonstrated burgeoning multi-sectoral and international interest in normative research on these technologies, and that work is moving at pace on the creation of standards and a plethora of guidelines and principles that can contribute to the regulatory environment of convergence technologies, and one which can uphold human values.

A review of the literature has informed the direction the OPTIMAI ethical and legal framework will take. The OPTIMAI project will primarily adopt the EU HLEG's "Ethics Guidelines for Trustworthy AI", acknowledging it as a preeminent European source of action guiding and operationalizable principles, whilst also cognisant of important developments resulting from the SHERPA and SIENNA projects and other initiatives. As such, the high-level principles adopted by OPTIMAI will be i) Human autonomy; ii) Prevention of harms; iii) Fairness; and v) Explicability, further translated down into specific requirements of i) Human agency and oversight; ii) Technical robustness and safety; iii) Privacy and data governance; iv) Transparency; v) Diversity, non-discrimination and fairness; vi) Environmental and societal well-being; and, vii) Accountability.

The existing literature offers early general guidance on the kinds of measures necessary to uphold the principles offered by the EU HLEG that provide a springboard for further research in the context of OPTIMAI, including (but not limited to) mitigation measures against coercion; the deployment of ethical and legal impact assessments; participatory design methods; environmentally sustainable design; methods for identifying bias in data sets; and appropriate accountability and transparency measures, including explainability of system outcomes.

The careful and deliberate application of ethical principles and their translation into appropriate ethical requirements in the context of OPTIMAI will be necessary to preserve or enhance positive relations between company stakeholders and meaningful work, which is to say work that gives workers purpose, facilitates social relationships, allows workers to exercise skills and self-development, supports self-esteem and recognition, and worker autonomy.

6 Conclusions

In this deliverable, a rigorous assessment of state of the art and existing results deriving from both related projects and research articles, was performed to identify those that are highly relevant to OPTIMAI. On this basis, EFFRA, as a dedicated industry-related projects association, was surveyed independently to identify all relevant projects on a per-case basis. Consequently, 15 EU-funded projects (mostly FoF-11 projects) were extracted and selected to be reviewed in this deliverable. The assessment was implemented in terms of functionality provided, innovation capacity, technology, status, etc. sparking at the same time co-operation activities with other projects, and even more, providing a starting point for T8.2.

A comprehensive state of the art analysis of research articles was carried out in relevant scientific domains according to participating partners' expertise. Among the explored domains were AI for Industry, Metrology, AI-enhanced Digital Twins, IoT sensors, Computer Vision and Augmented Reality, Quality Control, Predictive Maintenance and Zero-Defect Manufacturing.

As regards the articles selection process, a systematic literature review method was properly chosen to meet the objectives of this task. Although being a time-consuming process, the proposed systematic literature review method is well-structured and seems to be the most suitable for carrying out research. Thus, it allowed the incorporation of exclusive articles which were explicit to the subject of this systematic review.

The conducted process was focused on the most popular on-line publishers which offer open-access journal mining, including among others: IEEE, Elsevier, Springer, MDPI, IOP, etc. ScienceDirect and Scopus were also exploited as scientific and technical search engines for peer-reviewed journal articles and book chapters, covering a range of disciplines, from the theoretical to the applied. Furthermore, papers citing the identified works were also explored, to make sure that the latest progress was included. As a result, 122 articles in total, dated from January 2015 to April 2021, were selected and accordingly assessed to fulfil the state-of-the-art analysis.

Taking a close look at the produced outcomes, it is noted that CNNs (24%), ANN models (18%) and Deep NNs (17%) have shown significant contribution in almost all relevant scientific domains explored in this deliverable. More specifically, as regards smart manufacturing, Deep learning models are the most commonly applied models for image analysis, classification, object detection, recognition and quality control. Implementation of deep learning in imaging is mainly conducted via CNNs, as a relatively new and powerful technique to learn useful representations of images and other structured data. In particular, with the introduction of CNNs, features from vision systems could be learned directly from the provided data. On the whole, because of certain preferences in their structure, CNNs become powerful deep learning models for image analysis and quality control processes in production lines.

Due to the popularity of CNNs in vision systems, several applications of CNNs were investigated in the field of computer vision, quality control and defect detection in various manufacturing procedures. Other deep learning architectures like GoogleNet, AlexNet, ResNet etc. have also been applied in manufacturing for classification and visual analysis tasks. In some cases, AI-technologies are employed coupled with other mathematical models, like Decision Trees, Bayesian Networks, k-Nearest Neighbor etc., and form hybrid methods with elevated efficiency. Altogether, review studies and published articles in the last six years gather all the important, innovative, and most interesting applications of AI technologies.

The inclusion and review of a number of scientific studies as presented in this deliverable, contribute towards providing a comprehensive, well-structured overview of the most popular AI-based technologies that have been embedded lately in the process of Smart manufacturing aiming to improve system performance. Additionally, a plethora of challenges have been identified that need to be faced in the application of ML and Deep Learning techniques for Smart Manufacturing. These are mainly related to complexity and dynamic behaviors, data privacy and other security issues, as well as the selection or combination of the appropriate AI techniques and algorithms to handle various situations in the flexible manufacturing systems. Overall, this assessment provides the basis for triggering collaboration with other projects as well as it will yield further insights and connections to the next deliverables/tasks.

Following the technological challenges arisen with AI technology systems adopted in Industry 4.0, which mainly focus on privacy, safety, manipulation, transparency, fairness and accountability, certain considerations concerning the AI ethics have been made in OPTIMAI. On this basis, all the ethical principles required on the development of products and processes have been followed to provide an ethically acceptable and socially desirable framework which is in line with the expectations of people and the society.

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