AIM-NET

Artificial Intelligence in Manufacturing Network

ARTIFICIAL INTELLIGENCE IN MANUFACTURING

White paper

Executive summary

This white paper entitled "Artificial Intelligence in Manufacturing" reports the use of Artificial Intelligence (AI) in European manufacturing, and its potential to enhance competitiveness and technological leadership in the future. The paper is based on research conducted by the Artificial Intelligence in Manufacturing NETwork (AIM-NET), which represents the viewpoint of the manufacturing community on the achievements and challenges of AI solutions. The document covers topics such as AI in manufacturing processes, robots, machines, and operations support in manufacturing, and AI in manufacturing systems. It also includes discussions on cross-cutting aspects such as regulation, education, systems engineering, and data augmentation. The paper also presents the maturity achieved TRL levels of existing AI-based applications in manufacturing, typical KPIs used to assess performance, and barriers and limitations to wide adoption. It also provides a roadmap for future work on AI, with efforts needed in short-term and long-term time horizons. Overall, the paper provides a comprehensive overview of the current status and future vision of AI in manufacturing for policy makers, practitioners, and researchers.

Prepared by the Artificial Intelligence in Manufacturing Network – AIM-NET

info@aim-net.eu

Contributors

Laboratory for Manufacturing Systems and Automation, University of Patras, Greece

Sotiris Makris, Kosmas Alexopoulos, George Michalos, Zoi Arkouli, Alexios Papacharalampopoulos, Panagiotis Stavropoulos

AIMEN Technology Centre, Smart Systems & Smart Manufacturing, Artificial Intelligence & Data Analytics Laboratory, PI Cataboi, 36418 Pontevedra, Spain

Andrea Fernández-Martinez, Santiago Muiños-Landin

Flanders Make, Oude Diestersebaan 133, 3920 Lommel, Belgium

Klaas Gadeyne, Bart Meyers

CEA-List

Pascale Betinelli, Florian Gosselin, Caroline Vienne, Selma Kchir, Bianca Vieru, Guillaume Gallou

TECNALIA RESEARCH & INNOVATION

Mari Luz Panalva, Fernando Boto, Jose Luis Outón, Luis Usatorre

TNO Netherlands

Wico Mulder, Gu van Rhijn, Michael van Bekkum

National research Council of Italy - CNR

Andrea Orlandini, Nicola Pedrocchi, Alessandro Umbrico

Politecnico di Torino, Italy

Tania Cerquitelli, Enrico Macii

Fraunhofer IPA, Stuttgart, Germany

Marco F. Huber, Marco Roth, Danilo Brajovic

IMT Atlantique, France

Alexandre Dolgui, Simon Thevenin

Danish Technological Institute, Denmark

Mikkel Labori Olsen

Deutsche Forschungszentrum für Künstliche Intelligenz Gmb, Germany

Achim Wagner

Dipartimento di Meccanica, Politecnico di Milano, Italy

Bianca Maria Colosimo, Marco Grasso

MONDRAGON Corporation, Spain

Michel Iñigo, Joseba Bilbatua

IDEKO, member of Basque research and technology alliance, Spain

Gorka Unamuno, Iñigo Bediaga, Juanan Arrieta

Czech Technical University in Prague

Petr Samanek, Petr Kadera, Pavel Burget, Kolář Petr

VTT Technical Research Centre of Finland

Riikka Virkkunen

List of abbreviations

Abbreviation	Explanation
AGV	Automated Guided Vehicle
AI	Artificial Intelligence
EFFRA	European Factories of the Future Research Association
EU	European Union
GDPR	EU General Data Protection Regulation
GRU	Gated Recurrent Unit
H2020	Horizon 2020 - EU Research and Innovation programme
HMI	Human Machine Interface
HRC	Human Robot Collaboration
HRI	Human Robot Interaction
IoT	Internet of Things
IIoT	Industrial Internet of Things
LSTM	Long Short-Term Memory
RAMI	Reference Architectural Model Industry 4.0
ROI	Return on Investment
VR	Virtual Reality

1 Overview of AI in manufacturing

Manufacturing is traditionally an early adopter of technical innovation and digital transformation, which is also observed for AI related technologies. The ConnectedFactories 2 CSA project[1] has clustered the available AI solutions for manufacturing into the following six categories of technological enablers: Machine vision and Robotics, Embedded AI in Products (Smart Products), Machine Learning and Knowledge Discovery, AI Forecasting and Prediction, AI Diagnosis and Maintenance, Recommendation and Decision Support System. As for the maturity of AI solutions, the project has categorized it in five levels driven by the autonomy in the Human-AI interaction, which are namely the following: Humans in Control, AI Assistance, AI Recommendation, Collaborative AI, AI in Control (Figure 1). AI approaches have been tested for facilitating the design, planning, control, management, and integration of products and processes, and they are expected to empower companies to scale up and move from conventional manufacturing to autonomous factories. Relevant AI applications include cognitive systems and robotics, predictive maintenance, fault diagnosis and quality inspection, which have been enabled by AI algorithms such as Deep Learning and Artificial Neural Networks.

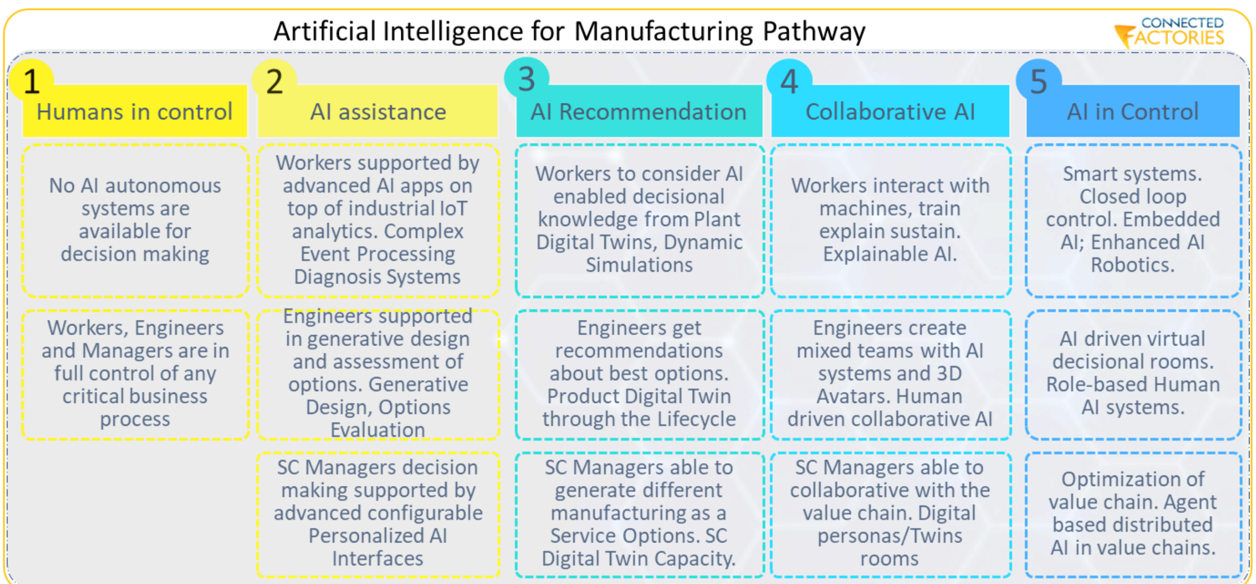

Figure 1. AI maturity levels from the human-ai interaction viewpoint, ConnectedFactories2 CSA project [1]

Even though several AI algorithms and applications are well-known, the status of the implementation of AI in manufacturing, as well as the unmet needs remain vague. A comprehensive taxonomy of existing solutions and manufacturers' expectations can improve the understanding of the AI achievements and the gaps that will stimulate the steps forward. AI-enhanced applications address varying requirements at different levels of the Reference Architectural Model Industry 4.0 (RAMI) hierarchy, which can be grouped into three levels: manufacturing systems, workstation, and manufacturing process (Figure 2). These levels are mapped to the RAMI model and include aspects from product and field devices to complete work centers and enterprise interactions with external instances.

[1] Connected Factories 2 Supported by the European Commission through the Factories of the Future PPP (Grant Agreement Number 873086) CSA, https://www.connectedfactories.eu/ai-manufacturing-pathway

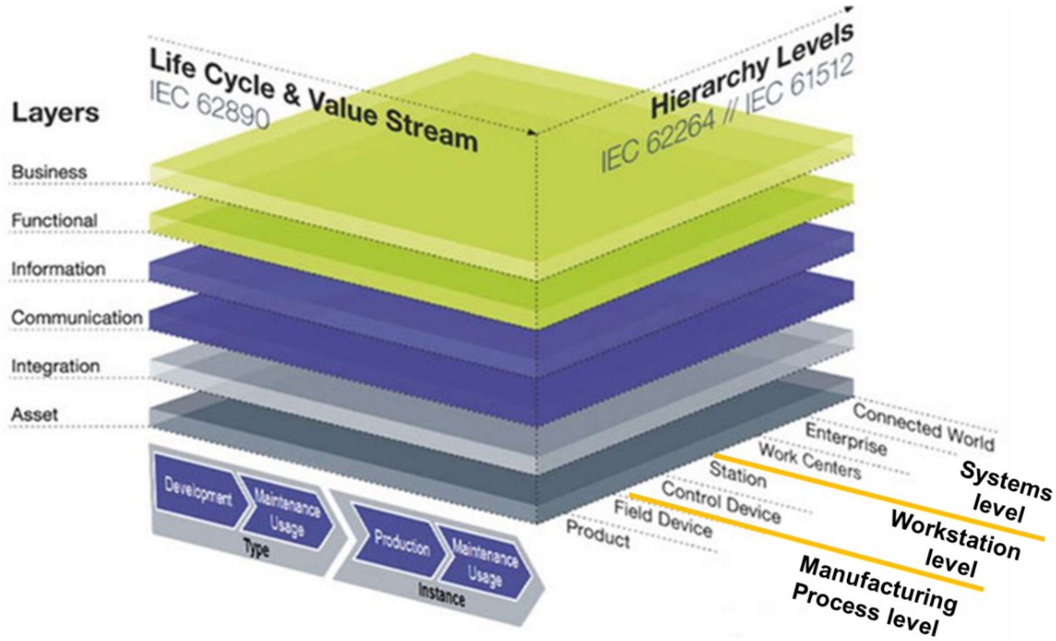

Figure 2. From the RAMI model to the Hierarchical model (adapted schema based on the Reference Architecture Model 4.0[2])

Each level is characterized by different complexity, i.e., number of components, correlations between components, parameters, and the like. In turn, the sources producing data, the data types, and the amounts of data that need to be collected, stored, and processed are different at each level. Furthermore, the decision-making horizon depends on the situation, and the level of decision-making. At the manufacturing process level, detailed decisions are required that should be made in near real-time, they usually affect the production of one product, and they are based on data of high certainty. On the other hand, at the systems level, it is needed to make strategic decisions for which longer time horizons are available nevertheless the available information is usually of limited certainty and the impact of the decisions can affect the whole company. Other requirements include the performance of the AI-based solutions in terms of runtime, latencies, human-in-the-loop to approve decisions, etc. Aside from the requirements that are relevant for each level, cross-cutting aspects also stimulate research around AI for topics such as Ethics, Explainability, Data availability, Legislation, Education, etc. Figure 3 provides an indicative list of research items that are relevant for each level, whereas sections 3, 4, 5, and 6 provide more details about the implemented solutions.

[2] https://www.plattform-i40.de/IP/Redaktion/EN/Infographics/reference_architecture_model_40.html

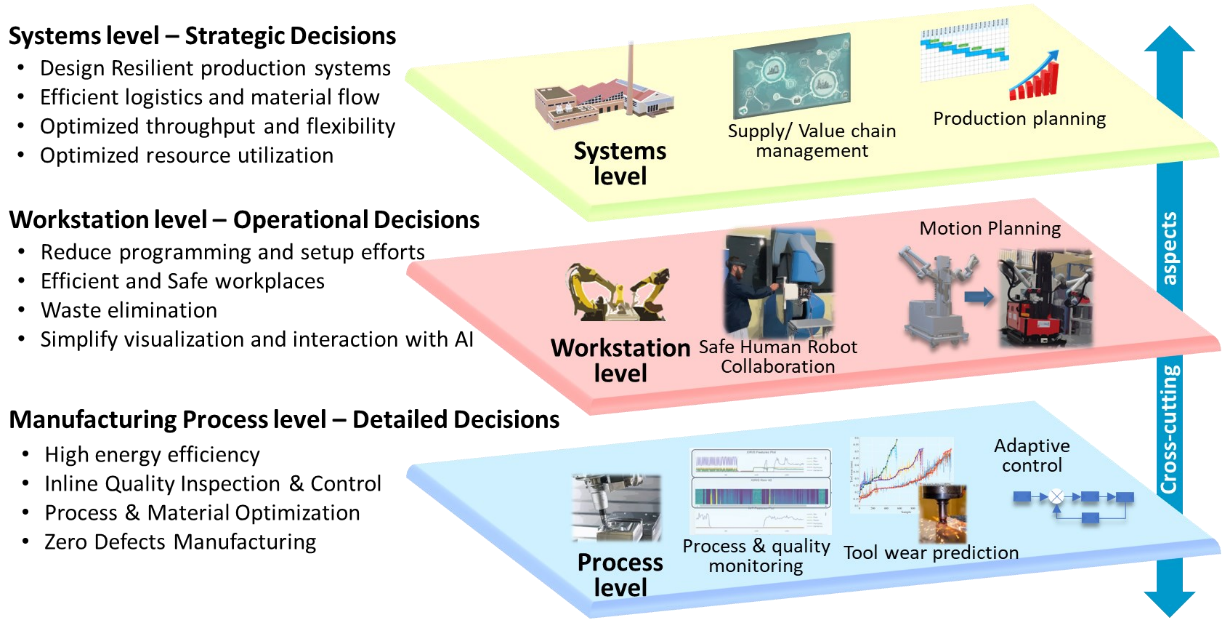

Figure 3. Industrial application areas and objectives for using AI in Manufacturing per hierarchical level (Chryssolouris, Alexopoulos & Arkouli, 2023).

Practitioners and academics have produced AI solutions for each of the hierarchical levels in manufacturing. As depicted in Figure 4, these solutions are often built-up to AI capabilities that have been typically incubated in other sectors such as the e-games industry, autonomous driving, language translation, etc. In turn, the AI functions such as computer vision, data generation, reasoning, and learning have been enabled by the application of AI methods. Based on Pedro Domingos AI methods can be classified into symbolic AI, connectionist AI, evolutionary AI, Bayesian AI, and Analogizer AI[3]. The application of AI in manufacturing has started with the use of symbolic AI in 1970s, however today the application of all the types of methods is met in the AI applications in manufacturing. It seems that the attention today is mainly on connectionist AI, where Convolutional Neural Networks algorithms seem to be amongst the most popular especially for machine vision.

[3] Domingos, P. Prologue to The Master Algorithm.

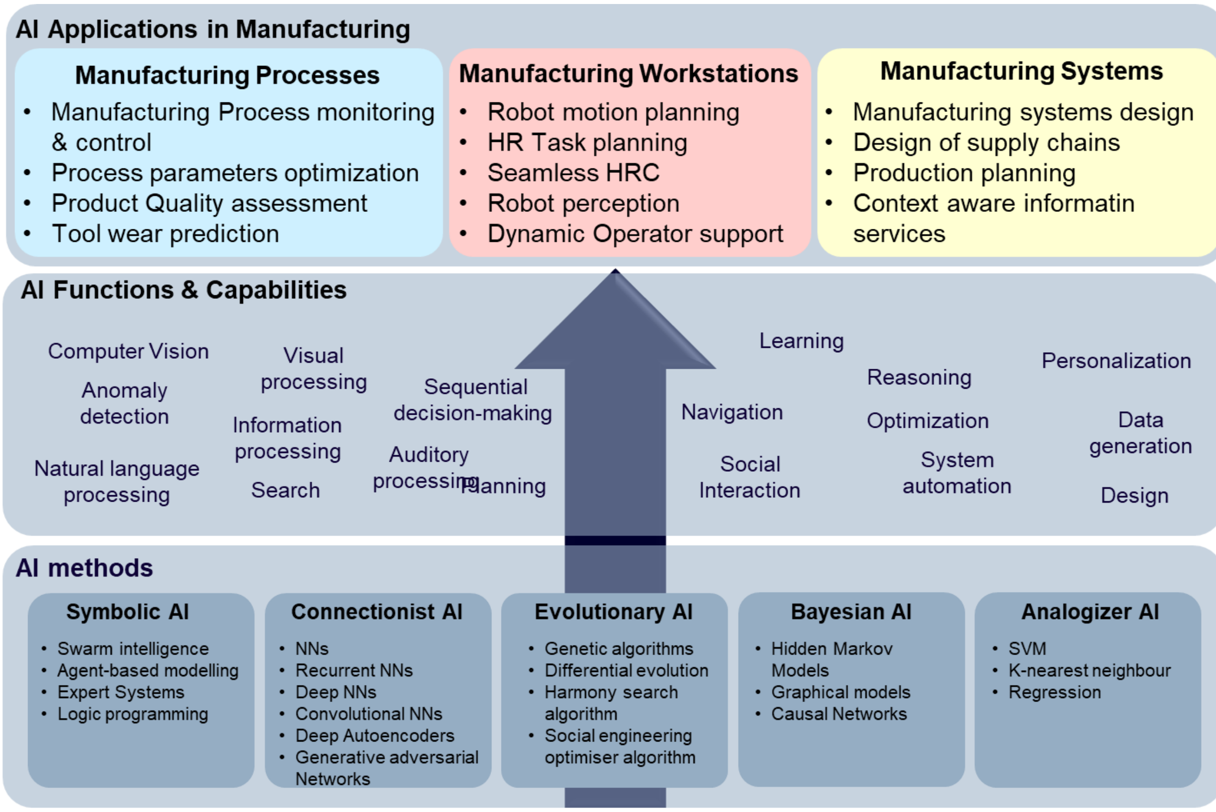

Figure 4. AI solutions hierarchy from basic AI methods to AI applications in Manufacturing

Figure 5 illustrates an indicative break-down of several application areas over the product/process lifecycle following the system, machine, and manufacturing process taxonomy. Additionally, a number of Key Performance Indicators (KPIs) typically used to assess the performance of the AI modules are demonstrated. Time, production rate, quality, footprint, worker's comfort, and user satisfaction in tandem with legal and ethical factors are some of the aspects that are frequently evaluated. Figure 5 also illustrates that solutions are usually designed to address a specific set of the lifecycle stages. On the other hand, the connectivity among the modules often relies on the humans, whereas the heterogeneity of the file formats of different design, engineering, and so forth applications usually undermines the use of data among different applications.

However, manufacturing is a 'wide' area of complex systems and sub-systems that are interconnected with myriads of dynamic connections. Manufacturing is achieved by a combination of processes, such as product and process design, production equipment design and commissioning, production, after sales, recycling and remanufacturing. Production itself is a complex activity that includes several resources and tasks such as dynamic scheduling, workforce management, warehouse management and many more.

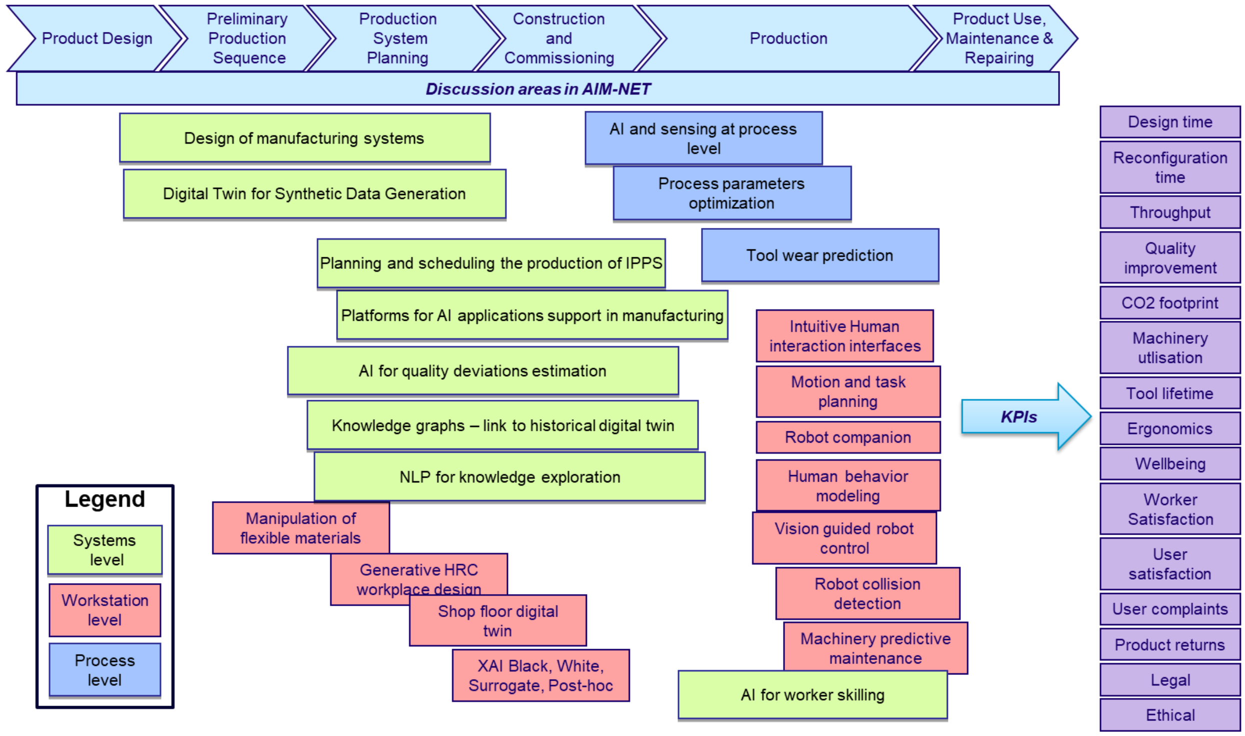

Figure 5. Overall map of AI application in Manufacturing. Horizontally are the Lifecycle stages of the Manufacturing system and Vertically the Physical Department involved in the creation of a product.

The limitations of the currently provided solutions derive of a series of barriers that have been reported to hamper the wider adoption of AI in industry, which are both technical and non-technical. In particular, technical issues seem to focus on but not be limited to access to quality data, management of large volumes of heterogeneous data, low traceability of the methods, and demand for faultless methods with low configuration and engineering effort. By means of illustration, Figure 6 aims to depict the complexity that arises in data management through the product/production lifecycle that involves several data types and formats. Different stages of the lifecycle generate new data of different types in different formats increasing the accumulated data that is produced and thus perplexing data management. The accumulation of data from product design to production and product use is illustrated with the number of boxes that increases from stage to stage. For instance, product design involves mainly the product drawings in CAD files, whereas production is based on CAD and CAM files, process plans, schedules, etc. that flow from the previous engineering stages, but also produce data from sensors, machines, and quality control.

Equally important are the challenges related to skills, trust, ethical and legal aspects, and vulnerability, whereas many manufacturing companies report a lack of relevant expertise to adopt AI methods. In addition, manufacturing companies are usually very experienced in buying machinery but when it comes to digital tools and AI, it might be challenging to find the right technology and estimate the return on investment. Also, the long lifetime of manufacturing infrastructure slows down the adoption of AI in production. The barrier related to trust and ethics are underpinned by the field of social AI. Understandability, explainability and trustworthiness are critical for the adoption and growth of the AI era. In general, it is deemed that people do not sufficiently understand technology or even the outcome or behaviour of AI in a human-comprehensible way. This limits the technology acceptance and the amount of trust from the bottom-up level since the adoption starts with a certain ground feeling of understanding and being understood. It is in human nature to want and be able to explain the behaviour of things in order to be able to predict and anticipate.

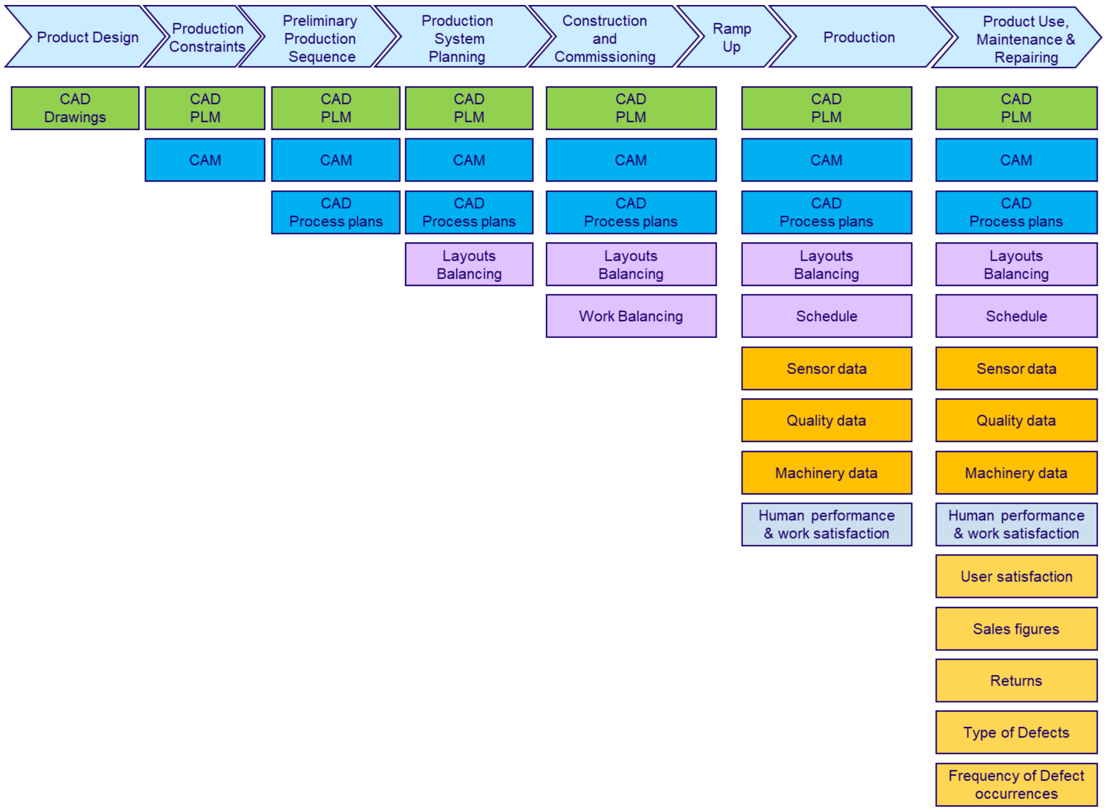

Figure 6. Evolution of Digital twin & data growth over the product/production lifecycle

The viewpoint of the industry stakeholders on the presented solutions and the expected next steps has been captured by several surveys. Indicatively, a poll from the EFFRA community indicated that the factory level optimization has the highest potential for AI in manufacturing, non-symbolic AI seems more important amongst the existing approaches, and the challenges regarding AI in manufacturing are related to AI and security, interaction of Humans and AI, explanatory AI, AI and business models, data availability, and finally digital skills[4]. Regarding revenue generation and cost reduction that can be achieved, Figure 7 shows that a limited number of responders can see benefit from AI in these areas[1]. Additionally, McKinsey & Company[5] conclude that Industry 4.0 has assisted companies improve KPIs in the following five areas of impact 1) sustainability KPIs (greenhouse-gas emissions), 2) productivity (as factory output), 3) agility (lead-time), 4) other speed-to-market KPIs, and 5) customization.

[4] https://cloud.effra.eu/index.php/s/4n4Y09ZvKnbfx1n#pdfviewer
[5] https://www.mckinsey.com/business-functions/operations/our-insights/transforming-advanced-manufacturing-through-industry-4-0

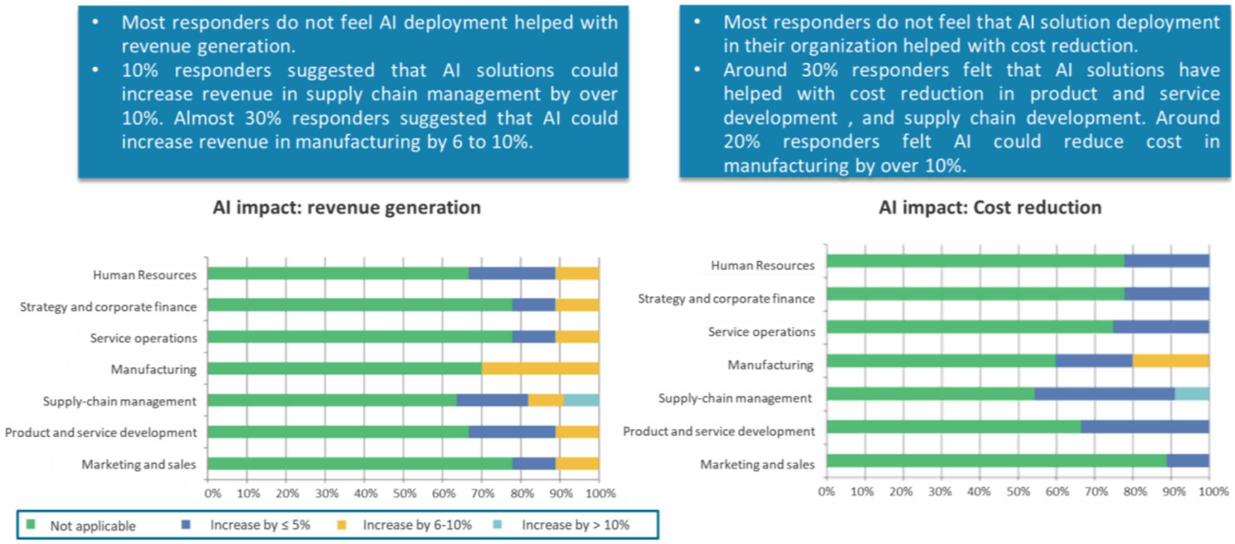

Figure 7. Survey on the revenue increase and cost reduction by AI adoption[6]

In addition to the existing surveys, AIM-NET has held a workshop on its own to directly receive feedback on the industrial perspective about AI. The scope of the workshop was mainly to investigate 1) the knowledge of companies about the AI capabilities, 2) why AI might have lower priority in the R&D activities of industries, 3) discover any gaps requiring the development of new AI-based applications, as well as investigate 4) how to promote AI among the industrial community. Additionally, it was of interest to explore the availability of AI-related expertise in companies and their current organization and identify whether guidelines on new education processes, expertise organization, and job design are needed. For instance, the adoption of AI may introduce different roles or extend the current ones e.g. line planners, autonomous robotics experts, vision experts, gripper designers, actuation analyst, and so forth. Furthermore, it was in scope to explore the expected impacts of AI and identify the ones that are more popular e.g., repurposing, resilience, quality improvements, lower emissions, reduction of operating costs, increase of industry competitiveness, etc.

The workshop was attended by industry professionals from several fields including automotive, aeronautics, electronics, manufacturing, and industrial automation. The workshop was organized in three parts: 1) presentation of ongoing AI-related activities, 2) structured discussion, and 3) open discussion on the interest in AI, AI adoption, barriers for adoption, successful implementations, and AIM-NETs potential contribution on enhancing the adoption of AI.

During the open discussion, a number of additional points were raised. Some points that were raised include but are not limited to the need of AI solutions for bridging the gap between manufacturing and product design and enriching discussions by including AI from the design perspective as well. Intelligent machines and exploiting data from the field are needed so as to optimize process parameters and avoid scrap, reduce waste, etc. A very important aspect is also the reduction of energy consumption, which can also be enabled by reducing the needed machine energy, e.g. by using models to reduce the energy consumption. Maintenance management is no data friendly, therefore AI-based support is needed and moving towards predictive maintenance seems very interesting. However, the integration of AI solutions is not yet wide due to the need for support of the management of different IT systems (e.g. it is often

[6] https://ai.eitcommunity.eu/assets/docs/EIT-UrbanMobility-Emerging-AI-and-Data-Driven-Business-Models-in-Europe.pdf

highly complex to clean up data). Moreover, the integration and (generalized) profitability of new technologies (XAI, quantum, surrogate models, security[7], cloud and big data[8], democratized & responsible AI[9]) is not clear. The output of the workshop has been summarized in Figure 8, where key points of the industry feedback have been classified in the following categories: 1. applications of interest, 2. existing implementations, 3. barriers, 4. AIM-NET expectation, 5.

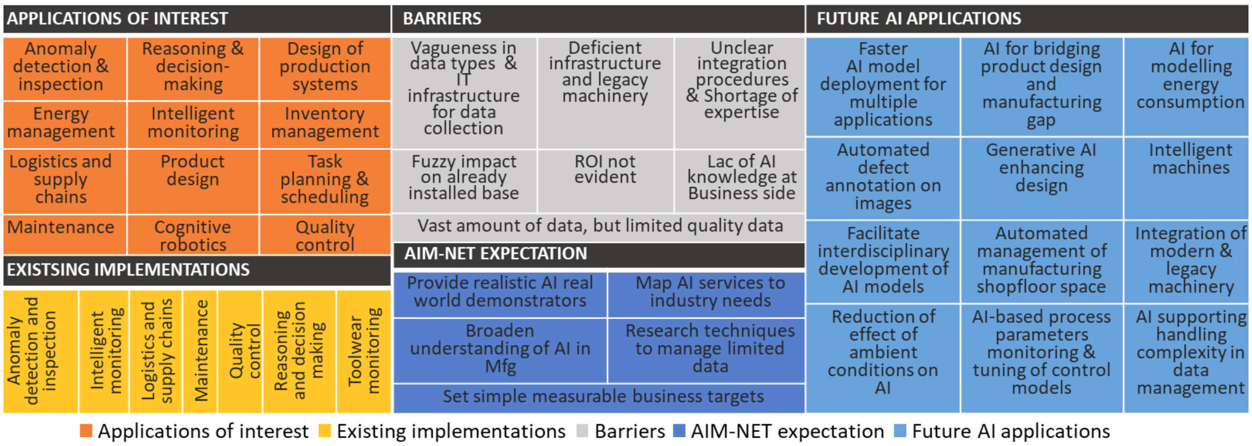

Figure 8. AIM-NET industry feedback

The existing implementations recap the areas where AI has already been used, and industry thinks the results are positive. Intelligent monitoring, anomaly detection and inspection, together with quality control, maintenance, as well as tool wear monitoring are the first cluster of implemented AI solutions. Additionally, reasoning and decision making as well as logistics and supply chain management are the second set of solutions.

The next step towards future implementation of AI is reflected in the applications of interest field. In more detail, intelligent production monitoring, inspection, and quality control anomaly detection, and smart maintenance reflect the need to further advance the functionalities already provided, and progress with processing large amounts of heterogeneous data towards reducing error propagation in the manufacturing chain and reduce downtimes and maintenance costs. The operation of manufacturing systems requires support in reasoning and decision making, with the worthiest to mention aspects being the inventory management, task planning and scheduling, management of logistics and supply chain but also energy management. Additionally, cognitive automation and robotics require AI-enhanced solutions to achieve the desired levels of efficiency. Finally, the design of production systems and products could also benefit from AI solutions.

Although the results so far are promising, the flourishing of the aforementioned AI-based applications in the industrial field remains uncertain. Topics that should be addressed to pave the way for broader AI adoption include among others many aspects that relate to the management of data from data sharing to infrastructures and old machinery along with the limited amount and quality of data. Human resources are also important for the adoption of AI thus, shortage of expertise hinders the adoption of AI. The reported technical barriers also include challenges that arise from the integration stage and also the

---
[7] https://www.marktechpost.com/2022/03/02/top-emerging-machine-learning-trends-for-2022/
[8] https://www.geekwire.com/2016/future-machine-learning-5-trends-watch-around-algorithms-cloud-iot-big-data/
[9] https://www.techtarget.com/searchenterpriseai/tip/9-top-AI-and-machine-learning-trends

uncertainty of impact on the already installed base. The non-technical barriers include but are not limited to the lack of AI knowledge at business side, as well as the obscureness around the expected ROI.

The needs for the step forward are expressed into the expectations from AIM-NET, which can be clustered into technical and non-technical subjects. For instance, broadening the understanding of AI in manufacturing, mapping the AI services to industrial needs, providing realistic or event real world AI demonstrators, and setting simple measurable AI KPIs and measurable targets are some of the non-technical expectations. On the other hand, research and techniques to manage the lack of data, e.g. the automated annotation of features such as defects on images, or the complexity of data and the management the integration of older to new IT systems. Additionally, methods are needed to enhance the design aspects, bridge the gap between product design and manufacturing, and enable to involve multi-actors in developing AI models. Nevertheless, methods to model deployment are also required. Moreover, AI solutions to serve for process parameters collection and model tuning in tandem with data and information visualization are indispensable. Finally, among others modelling the energy use and the manufacturing shop floor space availability are some of the applications that industrial stakeholders aspire to have in the future.

It is expected that the reported challenges will be gradually addressed towards realizing the Industry 5.0 in short-term, and autonomous factories in the long-term. In particular, in the next 5 to 10 years it is expected that AI will enable among others to perform automated optimization, widely adopt advanced manufacturing technologies, and deploy flexible manufacturing cells. In the upcoming paradigm of industry 5.0 it is expected that the body of knowledge coming from the fields of philosophy, cognitive psychology/science, and social psychology, will be infused in the industrial research fields, giving raise to the notion of trustworthy AI and thereby to the real adoption of AI in autonomous and hybrid factories. Additionally, the future *interactive data visualization* will become more automated, adaptive, and personalized to guide the manufacturing users in the visual analytics process and easily detect data changes, and the most relevant insights.

In the next 10-20 years, it is expected that with the help of AI, production systems could operate independently with little, or no human interaction and the digital supply chains would optimize themselves automatically. Regarding the Sustainability and Green aspects enabled by AI, production, supply chain management, and product design optimization are expected to provide several benefits. Production optimization may enable to produce more with less resources (energy, materials, human resources, …), produce more customized products with improved scheduling, improve availability of industrial equipment with predictive maintenance. On the other hand, supply chain optimization could enable us to adapt logistics to the production and the customer requests with low impact. Figure 9 summarizes the current state and goals for the future years.

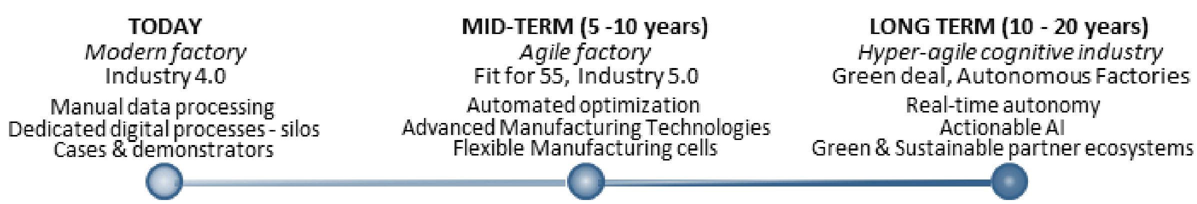

Figure 9. Mapping of the White Paper parts to AI applications maturity and Industry paradigms

Despite the described goals being well-known, the roadmap towards achieving them or even the research areas that should be promoted in order to enable this vision to seem currently obscure for the European manufacturing community. The discussion in the next sections aims to shed light on the capabilities of the AI-based tools that have been implemented, along with discussing in more detail the challenges, barriers, and limitations that are present at each level of the discussed hierarchical levels (manufacturing processes, workstations, systems), as well as the potential that are expected within the next 5-10 and 10-20 years. Subsequently, the roadmap for the future will be outlooked by prioritizing research areas that need to be further enhanced.

2 AI at the Process level

The manufacturing industry has a profound impact on economy and societal progress. Technological changes and innovations are essential sources for that progress; more profitable and efficient sectors and firms displace less productive and profitable ones. Thus, technological change is in the center of modern economic growth; as industrial production, is currently inspired by global competition. For that reason, there is a need for fast adaptation of production to the ever-changing market requests. This is a challenge, however, that is quite case-dependent. This implies the need for tailoring the solutions down to each case, not only from a technical point of view, since each machine and each environment are unique, but also there are business challenges to AI deployment, such as strategy enforcement (Lopez-Garcia et al, 2022).

The applicability of AI at manufacturing processes level has to do with many different aspects (Figure 10). To begin with, complexity manipulation, for the desire of the so-called Digital Twins is to be addressed, as the workflows have to be digitized. Then, more specifically, what could be required, potentially also as operations of the digital twins, are:

- quality monitoring, requiring to a large extent machine learning
- cognitive process control, where, depending on the sensors, deep learning can also be needed
- alarms generation and management, utilizing data science and AI (for instance heuristics or Genetic algorithms)
- Process control, where time-series can be utilized

The complexity is varying across applications and is dependent on many criteria, like:

- the process mechanism; for instance, conventional processes involve mechanical interactions and non-conventional processes thermal or chemical ones
- the sensor type; sampling rate may be a key parameter, or even the sensors plethora can lead to data variety
- the level of detail to which we are interested in; i.e., classifying the weld in the case of many types of defects increases the complexity
- and finally, the application itself; e.g., real-time (adaptive) process control requires smaller time scales than quality monitoring

All these facts can be summarized in the diagram hereafter, where the various techniques are matched against the needs for AI within digitalized process optimization workflow (Papacharalampopoulos et al, 2020; Panagiotis et al, 2020; Stavropoulos et al, 2020b; García-Díaz et al, 2018; Papacharalampopoulos et al, 2019).

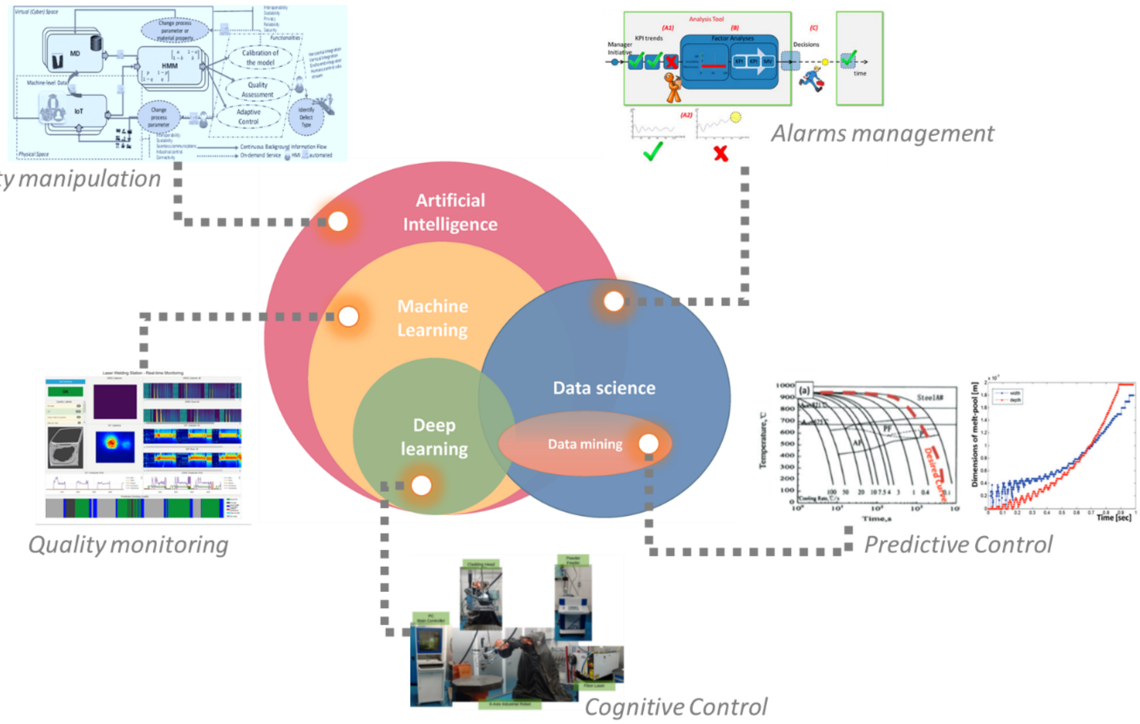

Figure 10. Manufacturing process level operations requiring Artificial Intelligence, (Stavropoulos, Papacharalampopoulos, & Athanasopoulou 2020), (García-Día, et al. 2018), (Stavropoulos, et al. 2020), (Papacharalampopoulos, et al. 2020), (Papacharalampopoulos, Stavropoulos, & Stavridis, 2018)

2.1 Intelligent quality monitoring & control

In any case, the various challenges that have been mentioned have to be addressed individually, as they are unique with respect to their theoretical and implementation-related needs. A very indicative problem that reflects this fact lies in the area of quality monitoring and link with process control. The characteristic factor is that everything must be done in real-time or at least near-real-time, especially in the case where the policy adopted is zero-defect manufacturing. This is slightly different than traditional quality control, i.e., six-sigma, in the sense that defects must be prevented; the table provides us with some extra details. Thus, everything must be done in time scales smaller than processing times and include countermeasures at the same time for every single part being produced.

The solution comes with the embedding of the concept of Cyber-Physical Systems (CPS) (Stavropoulos et al, 2020b). Also, I4.0 offers networking possibilities as its key ingredient; thus, AI can flourish here with related applications. AI is implemented in multiple CPS levels as indicated in the figure below (Figure 11), with some cognition characteristics than can even have distributed (networked) character.

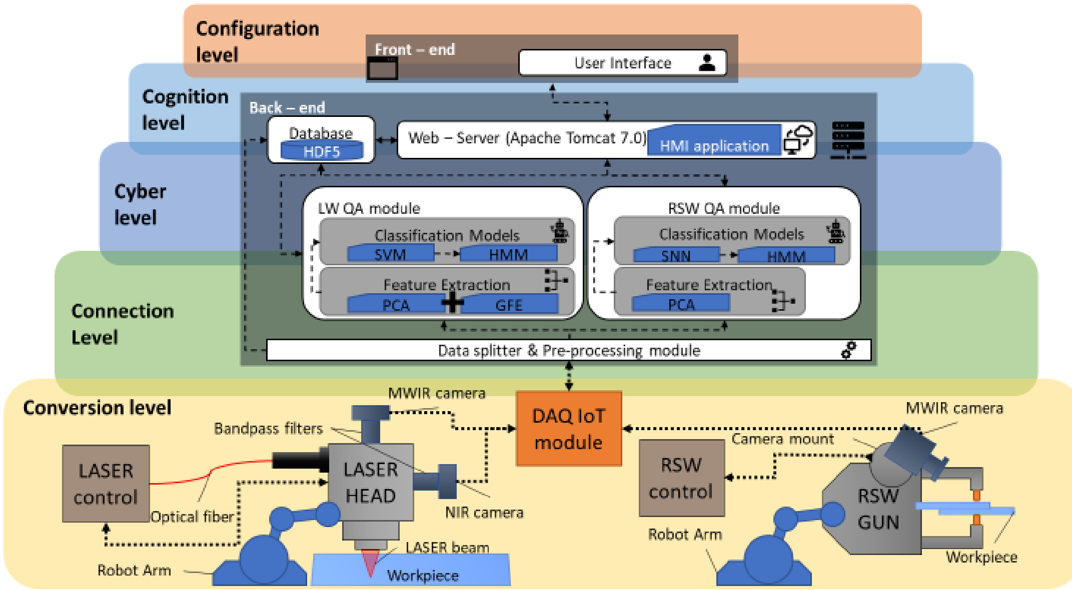

Figure 11. CPS aspects of quality monitoring and control, (Stavropoulos et al, 2020b)

It is also worth mentioning the diversity with respect to the elaboration of sensor data. The AI in the case of laser welding quality monitoring, for example, involves fusing data from different sensors, namely thermal images (or rather videos, since laser welding refers to seams) at different parts of the spectrum (Near-Infrared and Mid-wavelength infrared) which are then "reduced" down to features. These features can either be geometrical (GFE) or statistical (SFE). The first ones regard primarily the size of the melt-pool and the others have to do with pixels providing us with maximum information. Then, a classifier (Support Vector Machine in the case of Figure 12) uses these features as input and decides on the "frame" quality. The two extra steps have to do with fusing these decisions towards seam quality and part quality. Hidden Markov Models can be used to this end. Each one of these stages corresponds to integrating different I4.0 KETs.

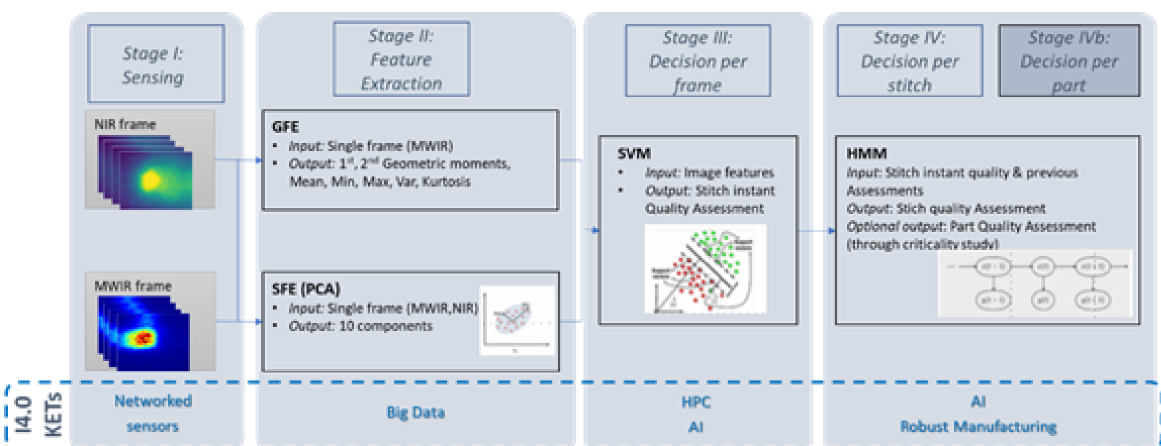

Figure 12. Hierarchical Quality monitoring digital twin based on AI techniques, (Stavropoulos et al., 2020)

An example of how AI can help process and quality engineers tackle the problem of fast and robust in-line detection of process anomalies is presented in Colosimo and Grasso (2018) and in Bugatti and Colosimo (2022). The application regards the in-line and in-situ detection of so called "hot-spot" events in laser powder bed fusion, one of most widespread metal AM processes in industry. A hot-spot is a local anomaly consisting of excessive heat accumulation as a consequence of diminished heat dissipations, commonly related to critical geometrical features, like overhang regions, acute corners and thin walls. Hot-spots are known to be drivers of geometrical and/or internal defects in the part, and hence they shall be detected as soon as possible. High-speed video imaging (in the order of hundreds or thousands of frames per second) can be used to determine the stability of the laser-material interaction during the exposure of the powder bed in every layer. The big challenge consists of being able to automatically detect the onset of a hot-spot event despite the highly time-varying patterns captured in video image data, minimizing the false alarm rate while maximizing the detection performances. Figure 13 shows an example form Colosimo and Grasso (2018), where a spatially weighted variant of the Principal Component Analysis (PCA) was combined with a K-means clustering-based alarm rule aimed at capturing the spatiotemporal signature of the process enclosed in the monitored video image data and detecting the onset of a local hot-spot. Indeed, pixels belonging to regions affected by hot-spot events were known to be characterized by a temporal cooling pattern that has high similarity within the anomalous cluster, but different from other video image pixels. The same problem was tackled by Bugatti and Colosimo (2021), by comparing the unsupervised k-means-based approach against other two AI-based monitoring solutions: one exploiting Support Vector Machines (SVMs) for the hot-spot classification, and one exploiting a fully connected neural network for the same purpose.

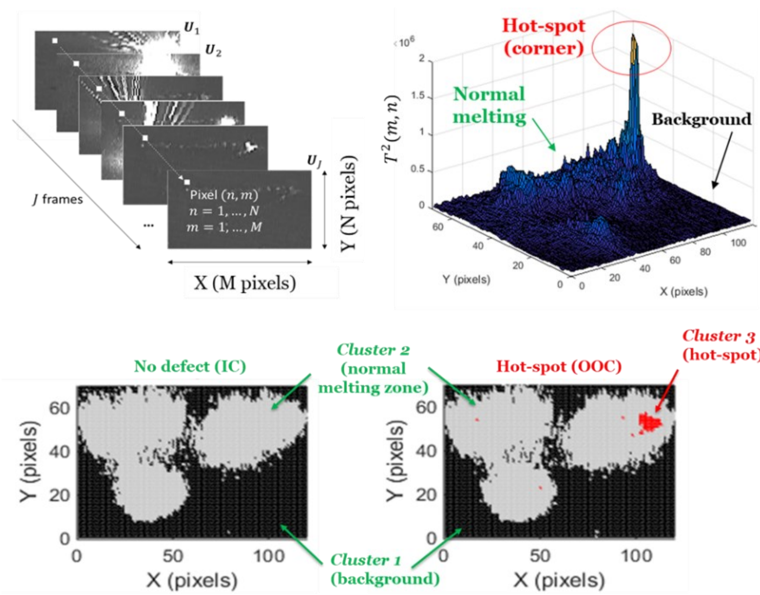

Figure 13. Example of hot-spot detection in additive manufacturing via spatial Principal component analysis (PCA) combined with K-means clustering (Colosimo and Grasso, 2018)

2.2 Tool wear assessment & prediction

Another class of problems is that of monitoring and predicting indirectly tool-wear. Tool-wear affects partially quality and in sensitive applications the part may be completely destroyed due to tool condition. However, the harsh environmental conditions (referring to process' environment) restrict the use of specific sensors, while the existence of legacy systems as well as the cost prevent the operators from integrating force sensors, in many cases. Thus, a solution would be to integrate sensors, such that vibrations and electric current one, that are only indirectly used to monitor tool-wear (Stavropoulos, 2016). So, the objective here is to monitor tool-wear indirectly and, if possibly predict tool-wear progression, while running the machine, through sensors, such as accelerometers and inductive clamps.

The procedure involves data collection from two different sensors, features extraction (i.e., spectrum related indicators). Subsequently, these features are fused, and a classifier based on thresholds for classes is used to decide on the toolwear level. Physics may be used to augment this (Figure 14).

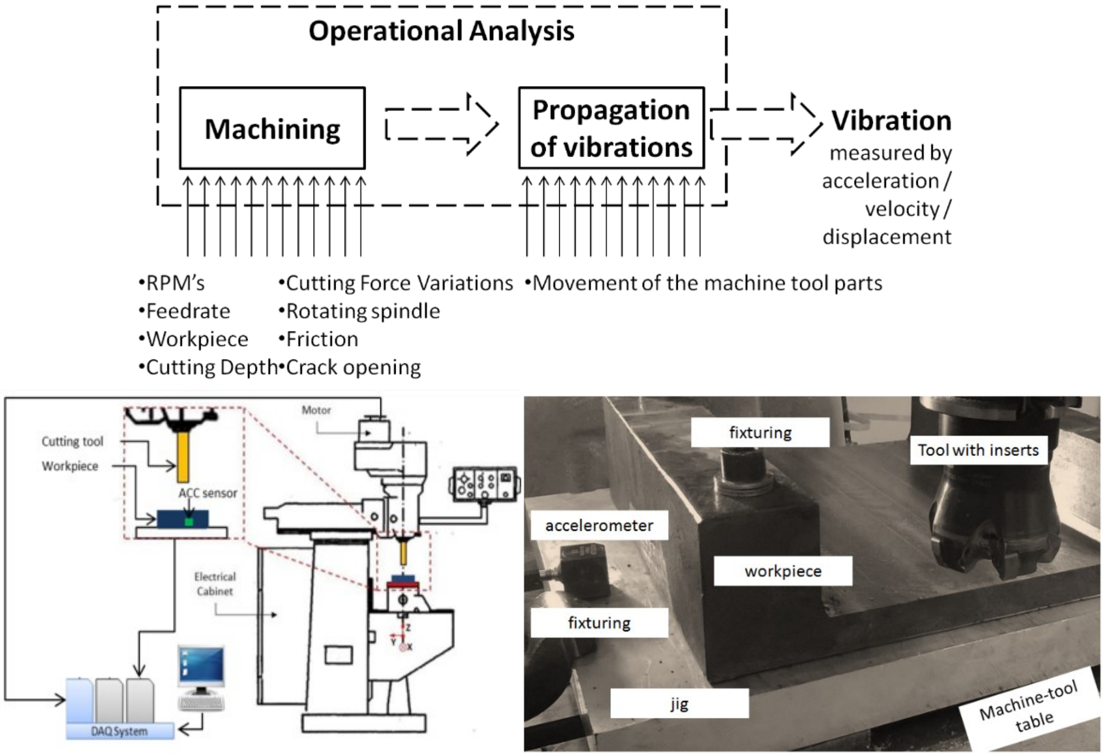

Figure 14. Toolwear assessment with physics-informed AI, (Stavropoulos et al., 2015)

The next step would be to fuse those results into a single diagram, using the features retrieved from these two signals. Acceleration feature and spindle electric current feature can be used at the same time to define thresholds separating low from medium and form high toolwear levels. The complex character of this application is revealed from the fact that the thresholds are typically not perpendicular to the acceleration or the current axes. As a matter of fact, they are also dependent on the cutting speed and they are not necessarily straight lines in some cases.

Despite the amount of literature devoted to studying multi-stream RNNs in machine tool monitoring, the powerful advantages coming from their application are underexploited in current applications. One example of their implementation for one-cycle-ahead multisensory data prediction in milling operations was presented in Garghetti et al. (2022) (Figure 15). In this case a Gated Recurrent Uni (GRU) neural network was used to predict future process outcome in different manufacturing scenarios, including the prediction of one-cycle-ahead of multi-axis spindle current signals in milling and the prediction of the machine health condition on the basis of periodically repeated no-load operations. The GRU network was compared against a wavelet modelling technique. Results showed that the GRU was more effective and accurate in predicting next process outcomes in non-stationary conditions, whereas in highly repeated and stationary process states, the most traditional wavelet method one preferred. This result also provides evidence of the fact that the actual benefits provided by AI strongly depends on the nature of the problem and the data pattern. The actual boundaries for convenient use of AI in place of other statistical methods is still not fully explored and consolidated and represents a relevant field of investigation.

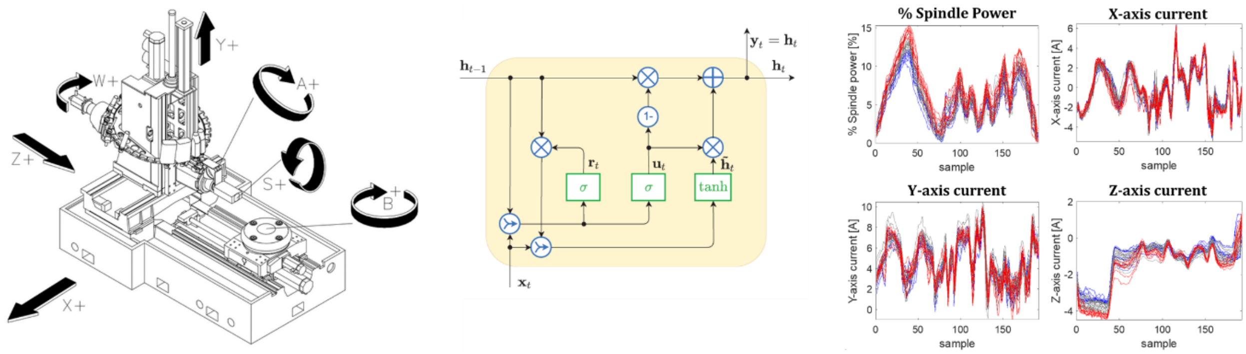

Figure 15. Gated Recurrent Uni (GRU) neural network for one-cycle-ahead prediction of process data in milling (Garghetti et al., 2022)

Tool wear prediction is an important factor which affects the machined surface characteristics, because during the machining processes those surfaces get more or less destroyed. Surface integrity is one of the most relevant parameters used for evaluating the quality of finish machined surfaces. The predictions of tool life in machining have become a challenging task for proper optimization of the process, mainly because they play an important role in the economic aspects of metal cutting operations. Machine learning regression techniques can be used to predict the tool wear using as predictive or input variables the cutting force components.

2.3 Smart modelling & digital twins

Moving on to a different class of potential operations within the framework of a digital twin, integration of AI in process modelling is required to keep up with the various aspects of a digitalized workflow. To begin with, AI could be used to accelerate theoretical (physics-oriented) process models, towards their running in near-real time (Foteinopoulos et al, 2018). Their use could be multifold; responding to what-if scenarios, designing process control, or even studying the inner state of a part (i.e., in terms of quality). It is also noted that the concept of “near-real time” (decision making or optimization) refers to being able to react to optimization requests within a fraction of process time.

An additional example would be utilizing a set of models seamlessly, in a way that is able to provide uncertainty management and process control for manufacturing processes. It is seen in (Stavropoulos et al, 2021) that at least four different models are cooperating to achieve this. At the same time, AI can be in charge of the workflow and the exchange of information among the aforementioned models. This results in a complex CPS that is a result of rather severe integration, as per the guidelines that have already been given. Then, with the help of process control, a variation of classical control theory, the behaviour of the process can be regulated within the desired specifications (Figure 16).

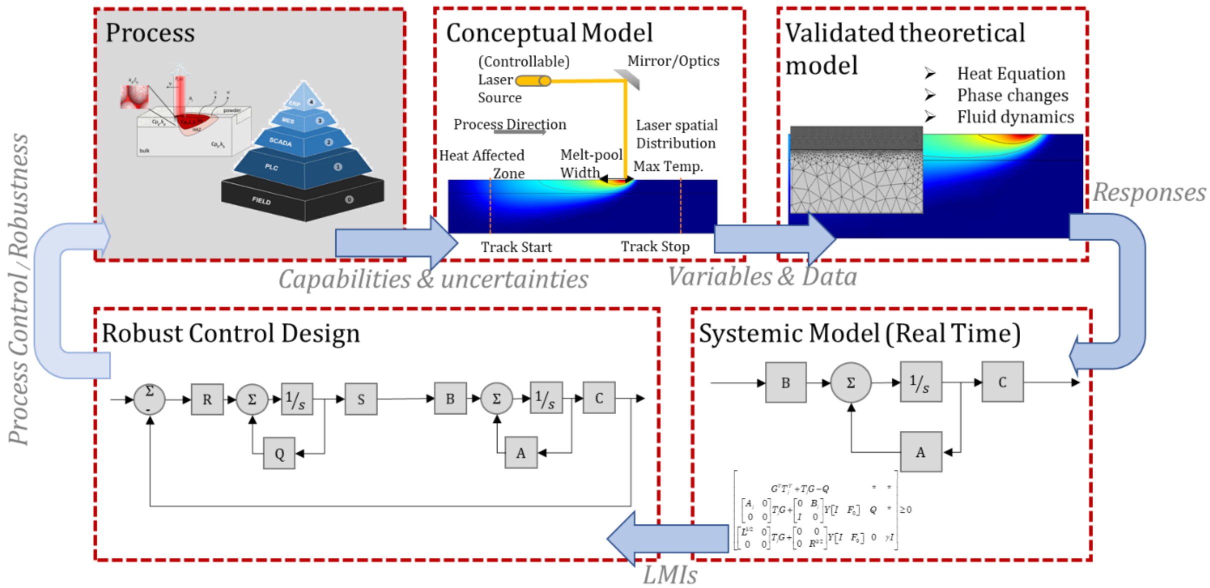

Figure 16. Robust manufacturing implementation, (Stavropoulos et al., 2015)

The augmentation of a digital twin towards ZDM is also potential with the help of AI (Papacharalampopoulos et al, 2021). The use of AI at process level, however, does not end here. In modern manufacturing, multi-criteria optimization is a major demand, given the environmental and social challenges. Energy and quality joint problems occur this way and AI, besides optimization and control could intervene also in hierarchical use of process models; the case of molecular dynamics is characteristic (Panagiotis et al, 2020); local information has to be fed to higher-level process simulations, providing extra information about the KPIs.

Finally, as enlisted at the beginning, energy, quality, or any other KPI related alarms can be manipulated through AI. The fusion of AI with theoretical models is a powerful tool; in the following figure, a very specific illustration is given, for the case of an FDM 3D printer (Papacharalampopoulos et al, 2021b). It can be seen that, depending on the direction of planar printing, the energy consumption may have some differentiations. It is up to AI to decide if this has to trigger an alarm and a suggestion on whether this is an issue of the printer (process), or the monitoring system itself.

2.4 AI for Process optimization

Process optimization requires adequate knowledge about a wide range of parameters and variables that impact the process results. Optimization of industrial processes should be a task for industrial process experts. The complexity of the processes has required the help of mathematical techniques able to manage huge quantity of data that extract the intrinsic relations and keys that are hidden in those data. Likewise, the complexity of these mathematical techniques requires the participation of data analytics engineers to help the industrial process engineers. They have to cooperate in order to disentangle the industrial process keys hidden in the data, but this complementary work is not always efficient. In the end, the ideal situation would require only industrial process experts, and so, the question to be faced would be: is there any possible approach to provide the industrial process experts with the necessary tools to optimize their process?

The first stage is always to understand the details of the industrial process, which is specific of every industry (Figure 17). Once the process is understood the next stage is the modelling of the process, setting up the prediction model to estimate the desired key performance indicators (KPIs) based on the relevant process parameters (PPs). Once the prediction model is set up, the final stage is the optimization one, where one or more combination of process parameters is selected to reach an optimum KPI.

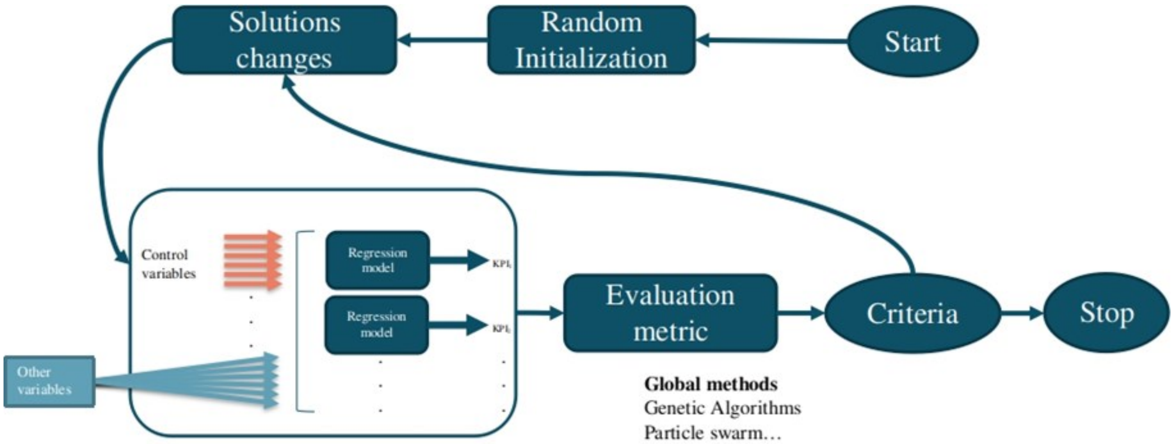

Figure 17. Optimization framework for decision making in manufacturing

In the case of process parameters optimization, the ultimate goal is to produce high quality products with less cost. Meta-heuristic AI algorithms such as, genetic algorithm, simulated annealing, particle swarm optimization, artificial bee colony optimization and ant colony optimization can be used. The aim of these optimization problems is to find the best combination of process parameters in order to optimize a KPI related to the process efficiency. In some cases, various criteria can be used simultaneously, turning the optimization problem into multi-objective optimization problem. Also, some constraints are usually used to assure that the quality requirements of the final product are fulfilled. Due to the complex nature of the processes, the modelling of the KPI (objective function) and constrains are usually performed using data-driven models instead of employing simple linear functions.

An additional benefit, as stated also, in section 3.2, is the complementarity with physics modelling. For instance, even part of modelling could be substituted by AI. In the case of spring-back modelling in particular, the proposed mechanism uses a novel point series representation to capture local geometries that then form a global bank of geometries for general use. Each point series can then be associated with a predicted springback value generated using deep or machine learning. Experiments are reported using a Long Short-Term Memory (LSTM) model coupled with a Multilayer Perception Network (MLP), and a Support Vector Machine (SVM) regression model (Bingqian et al, 2022). There have also been attempts to develop a visual evaluation method to diagnosis the quality installation of blind fasteners with AI (Del Val et al, 2022).

The customization in data elaboration is obvious, since the machines are subject to unique surroundings, leading to customized noise. Subsequently, technical challenges are to obtain more reliable models in order to reduce the uncertainty of the data by applying more sophisticated AI techniques. As such, generative adversarial networks can be used to balance the distributions of the target data that usually do not present too high or too low values. In addition, data management calls for a whole different class of IT backbone. All these imply, in addition, the use of a differentiated workflow during both design and operation phases. This causes specific business hinders in the industry operation, since there are financial, social and communicational challenges that are formed from this technological transition. Another issue here is to imply actively the human (operator) in the loop. This would help to have more supervised data of the process, thus having more certainty and robustness in the data.

In some industrial processes, there are variables which are difficult to measure on-line due to technical or economic limitations. A solution for this type of problem comes on the hand of the software sensor (SS) paradigm, which provides a reliable and stable estimation. A soft-sensor is a predictive model which is responsible for the online forecasting of certain variables that play an indispensable role in the quality control of an industrial process. In this paradigm we must include the fact of the degradation of the predictive model. Therefore, it is necessary to consider and plan a continuous readjustment through the detection and retraining of the model.

2.5 Utilization of data in process design and operation

Generative models, as a particular technique within the AI landscape is a relatively new field whose applications are growing each year in different domains. The techniques englobed under this term, such as Generative Adversarial Networks (GANs) (Goodfellow et al, 2014) or Variational Autoenconders (VAE) (Kingma et al 2020.) are widely used for data generation or dimensionality reduction problems in fields such as medicine (Uzunova et al, 2022), chemistry (Dan et al, 2020) or material science, and recently Manufacturing frameworks (Kim et a, 2021) started to adopt also these non-supervised solutions for particular problems. Apart from the most obvious application of Generative modelling for the design of products, also performance-oriented materials or design synthetic data generation has been demonstrated as a remarkable solution for data augmentation.

One bottleneck for the efficient application of some ML techniques that rely in the use of Artificial Neural Networks (ANN) is the large amount of data required for training. In particular, many Quality Inspection procedures are based on Convolutional Neural Networks (CNN) for image processing that need large number of images for it. Given that factories try to minimize the existence of defects, the acquisition of large numbers of images of defects tends to be difficult. In addition, defects usually appear in a way that can be classified by some common features meaning that different defect typologies can be identified for the same process and the frequency at which the different typologies appear is usually different. Which means that examples of some defect typology can be massively acquired and examples of some other can be rarely seen. As a result, quality control procedures might show really good results for some typology while remaining almost blind to the detection of another. The use of generative models to generate synthetic image data for training of such CNN-based systems allows significant enhancement of the volume of data for training with its consequent impact on the detection ratios. This type of application is probably the most mature application of generative models reaching TRLs between 5 and 6.

Another application of generative models includes product design. Specifically Deep Generative Design tools such as Generative Adversarial Networks (GANs) and Variational Autoencoders (VAE) have been shown as powerful frameworks to provide solutions in a wide range of complexity dimensional reduction problems and generation as active tools for 3D shapes generation of specific products (Figure 18). This application of AI can enhance the co-creation of fully customized products can be achieved though the exchange of data and processes between members of a community (Ding et al, 2013; Duray, 2002; Mohajeri, 2015). This is the essence of social manufacturing (SM), a novel approach where such data is shared within a cyber-physical social space (CPSS), triggering massive decentralized co-creation processes.

One can visualize the cyber-physical social space as a multidimensional one, with multiple channels holding information flows in terms of services, technology or design each of them with different degree of explicitness regarding agent (community member) knowledge. One key element within the SM landscape is the so-called *prosumer*, a consumer that participates actively in social manufacturing assuming also the role of a producer. The more involved the prosumers (agents), the more reach the final product results through self-organizing and social-enabled mechanism. However, contrary to what would be an ideal SM context, where all the members of a community are pure prosumers, the current approach to SM shows the presence of customers and services providers in an independent way. In such scenario, the symmetrical conditions of the assumed roles distribution, or the fact that all the actors might not be equally active, results in a potential weakness of the whole SM workflow for the emergence of a collective production.

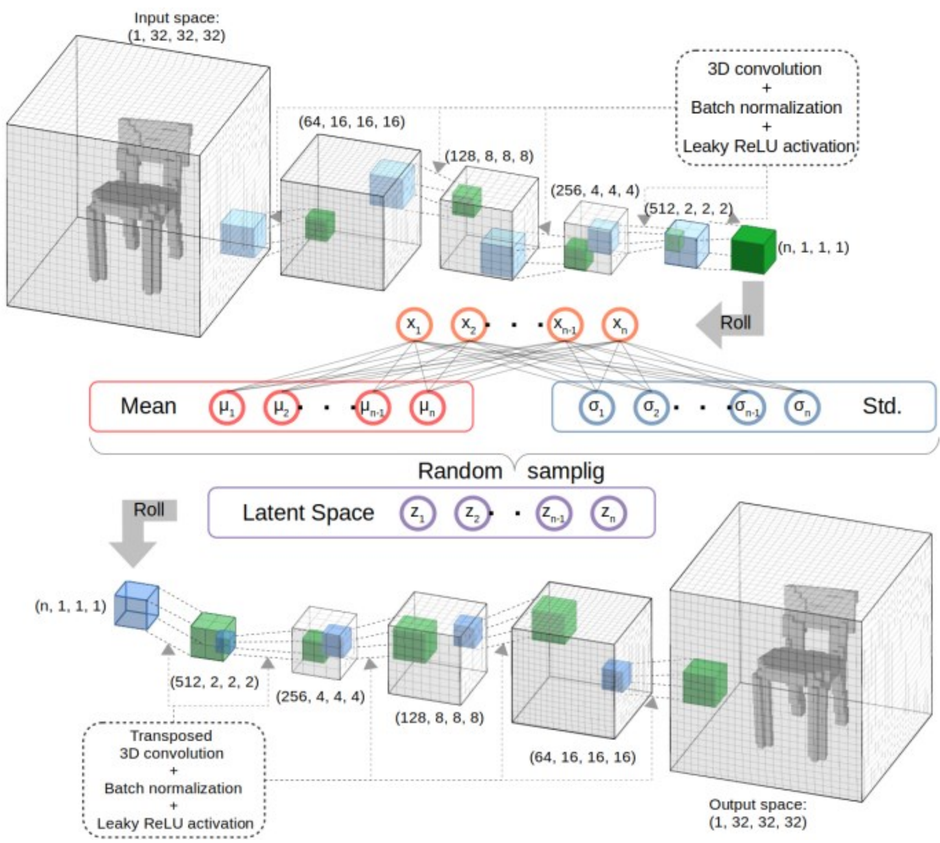

Figure 18. Generative Design in manufacturing, (Gonzalez-Val and Muiños-Landín, 2020).

In order to achieve customization of products based on collective behavior, one particularly critic channel that captures the interactions within the CPSS is the one composed by the information related with product design. Such criticality comes not just from the above-mentioned risks regarding the possible absence of agents providing such knowledge to the CPSS. But also, from the intrinsic difficulty to define variables that hold the essence of a design, to represent it as information to be stored, shared and customized. To overcome such issue Artificial Intelligence provides different approaches (Gonzalez-Val and Muiños-Landín, 2020), as shown in Figure 18. The application of Generative approaches in this domain rely on a very experimental phase with TRLs between 3 and 4.

Complementarily to the AI-based design of customized products, AI has enabled to promote the fast and inexpensive production of such products. Manufacturing companies need to meet the customer demand for products tailored to specific, individual needs, which in turn introduces the challenge of design and produce fast and cost-efficiently easily adaptable goods of high quality. The development of modular design architectures has proven capable to meet this challenge. In this perspective, novel AI-based clustering methods have been developed to cluster product's components into modules towards the effective creation of modular design architectures (Pandremenos & Chryssolouris, 2011). Neural Networks in combination with Design Structure Matrices and multi-criteria decision-making approaches have been used to reorganize the components of a product in clusters to efficiently generate and evaluate different clustering alternatives (Figure 19).

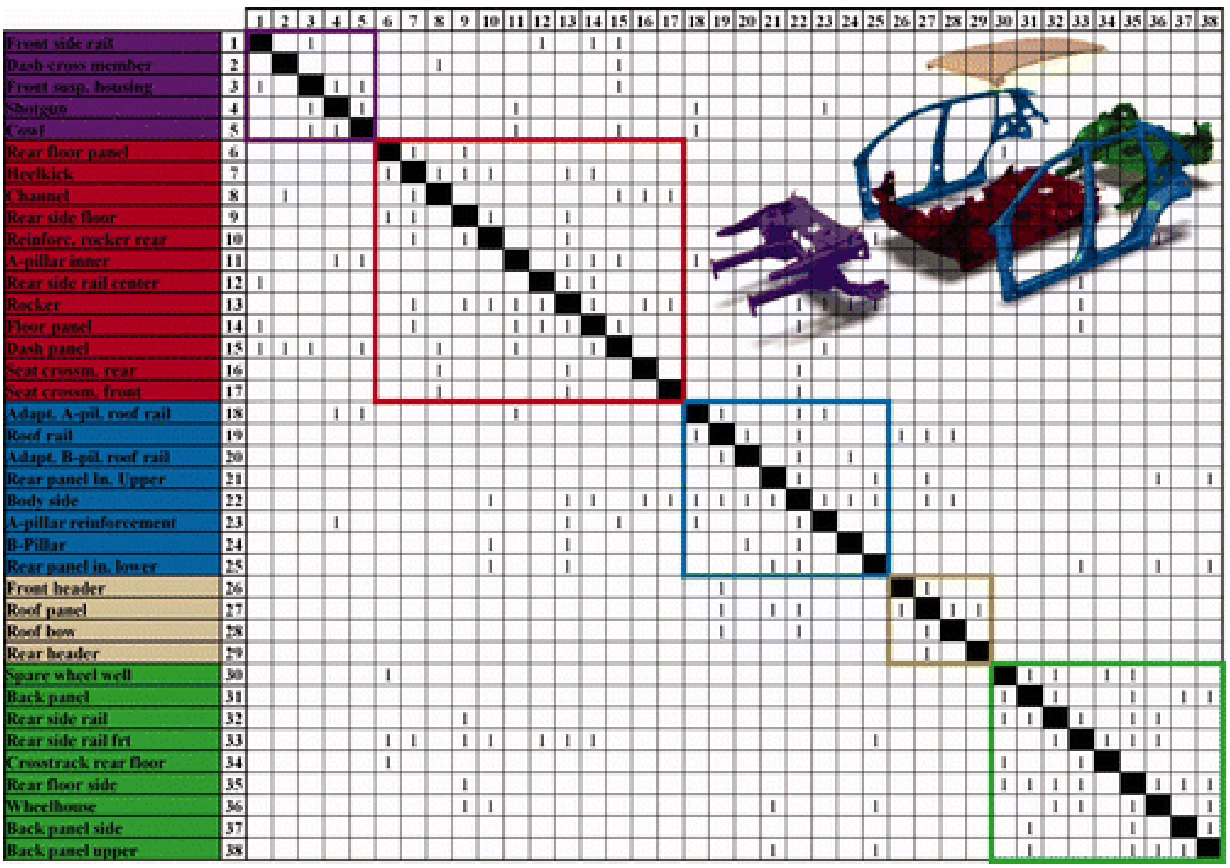

Figure 19. Design Structure Matrices for Body in White (Pandremenos & Chryssolouris, 2011)

Furthermore, generative approaches have been used for the development of high-performance materials. High-performance materials are a key tool for several reasons. On the one hand, their use brings obvious progress in the performance of the pieces where they are used in fields such as aeronautics, construction, or biotechnology. On the other hand, high-performance materials also allow more efficient use of energy in industrial processes where the use of such energy becomes intensive with its consequences in terms of environmental and economic sustainability. For these reasons, the emergence of high-performance materials has captured the attention of industry and researchers within the last years. However, the development of these materials requires a large amount of time and money invested in the design, synthesizability evaluation, construction, and characterization of such compounds. The use of AI for the design of materials, even in its current infancy status, provides a valuable tool to accelerate the initial phases of materials design and HEAs, where the high number of combinations brings a perfect scenario for the deployment of Machine Learning techniques. In this context, Generative models start to be used to generate synthetic compounds or alloys for highly intensive industrial processes. In this scenario, the application of Generative models relies in a very initial phase due mostly to the implications of its deployment. Meaning that this technology in this domain remains in a TRL between 2 and 3.

The nature of the algorithms themselves makes generative approaches difficult to quantify or to stablish standard indicators that might quantify their performance. However, depending on the application some KPIs can be established for the solutions developed using generative approaches. For instance, in case of using Generative approaches for data augmentation, the improvement of the performance of the algorithm for which the data is generated for, is a direct measurement of the impact that the generative approach is having of the global system. In the case of using Generative models for materials design, one indicator of its performance is the number of compounds generated within the requirements stablished by the case of study. The most difficult scenario to evaluate the performance of the generative model is the design case. Here, if the design implies certain functionality, again the amount of candidate solutions within the requirements constraints can be established as an indicator. However, if the design is provided in a creative context, only the variability within the latent space can provided hints about the performance of the algorithm.

2.6 Consolidation of AI application at the process level

The use of AI in the scope of manufacturing process optimization is a multi-fold issue, that affects every other operation, and can result in overall KPIs enhancement. However, this multi-objective optimization does not come at no cost. The implications in the technical workflow, as well as in the business operation can cause some turbulence that requires for some steps, not necessarily in a linear scenario, but rather in an iterative way:

a) Selection of monitoring systems
b) Choice of data management system
c) Standardized Data structure/format
d) Document physics-based knowledge, due to materials and geometries interaction
e) Choice of AI model
f) Selection of way of giving feedback to the system
g) Define the role of humans
h) Training the system
i) Train the personnel
j) Operation with a different workflow
k) Evaluation of the AI system with respect to the requirements

The implementation of AI at the manufacturing process levels has provided several benefits including reduced assembly time and easier automation solutions, improved quality control and detection of process deviations, increased overall throughput, and decreased NDT inspection. For instance, AI has shown to be a reliable option for controlling manufacturing processes and improving efficiency for fastening processes. The technology has achieved high scores in laboratory trials, but it is currently at a TRL level 4. Additionally, using AI in fastening can have a positive impact on sustainability by reducing the weight of aircraft and reducing fuel consumption, CO_2, NO_x, and noise emissions since there are about 1.5-2 million rivets and bolts in a large aircraft [10].

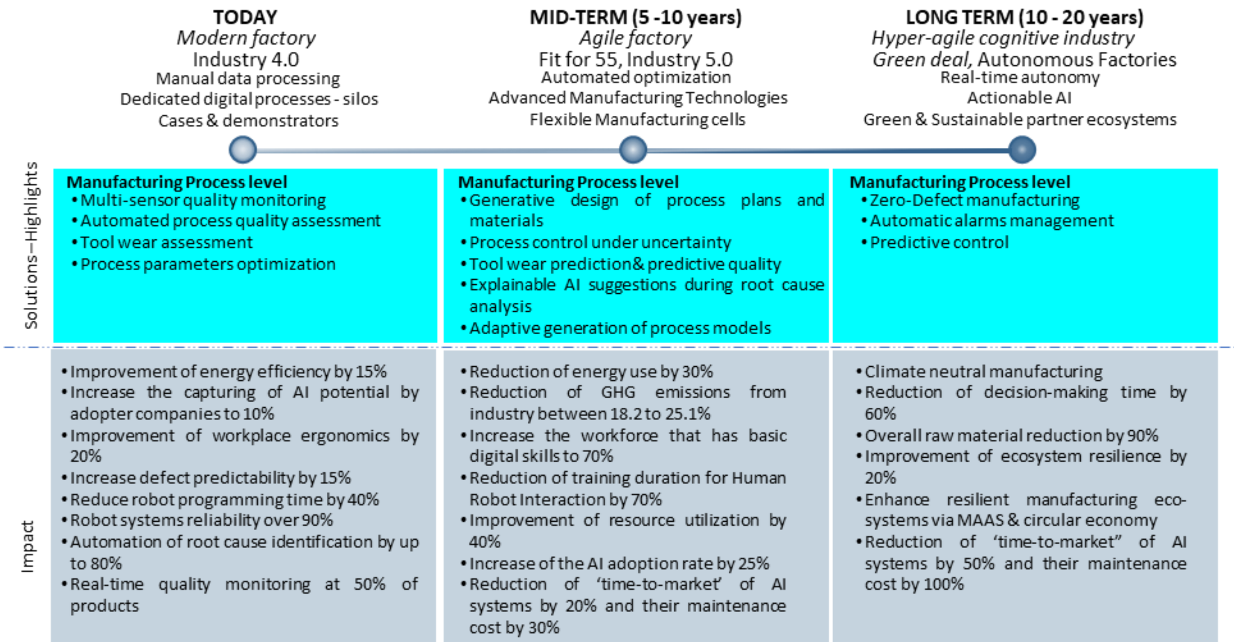

Figure 20. Current status and Future Vision for the adoption of AI at the Manufacturing Process level

Over the next 5-10 years, it is expected that AI-based solution at the manufacturing processes level will become increasingly integrated into automated processes reducing substantially processing waste and energy use. Over the next 10-20 years, it is expected that the technology will continue to evolve and improve, leading to even greater benefits and improvements in energy efficiency, raw material use, and sustainability.

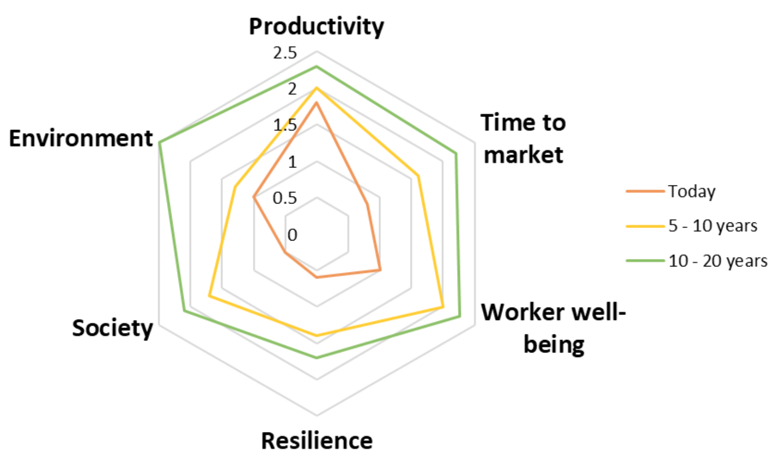

Figure 21. Degree of vision achievement

[10] Biao Mei, Zengsheng Liang, Weidong Zhu, Yinglin Ke, Positioning variation synthesis for an automated drilling system in wing assembly, Robotics and Computer-Integrated Manufacturing, Volume 67, 2021, https://doi.org/10.1016/j.rcim.2020.102044

3 AI at the workstation level

The increasingly growing requirement to accommodate the fluctuations of market demand along with the trend for highly personalized products has also influenced the configuration of manufacturing workstations. So far, automation has enabled increasing production rates and quality consistency, reduced production costs, and achieving competitive delivery times. However, further advancement is needed in the selection of the automation degree and the work cell configuration since automation and flexibility are usually inversely proportional. To this end, cooperating machinery has been proposed meaning the cooperation of pieces of machinery equipment between themselves, but also the cooperation of machinery with human operators (Makris, 2021; Arkouli et al., 2021; Michalos, Kousi, et al., 2018). Therefore, the potential of AI-based tools to facilitate the implementation of collaborative production systems where people, robots, and parts coexist is investigated as a means to realize the new Hybrid Production paradigm (Figure 22) is discussed.

This coexistence of humans and robots induces several decision-making problems related to the design, planning of operation, and control of the workstations (Michalos et al., 2022). For instance, layout design, task allocation, coordination of the resources, adaptation of the behavior of the automated resources to the requirements and needs of the individual workers, adjustment of the behavior of the resources based on the status of the process and environment, and so forth. On top of that, Human-Robot Collaboration (HRC) entail challenges in physical interactions, i.e. always guaranteeing the safety of human operators, and activities coordination, toward improving cell productivity. Hence, robust controllers capable of preserving productivity and enforcing human safety are required (Freitag & Hildebrandt, 2016).

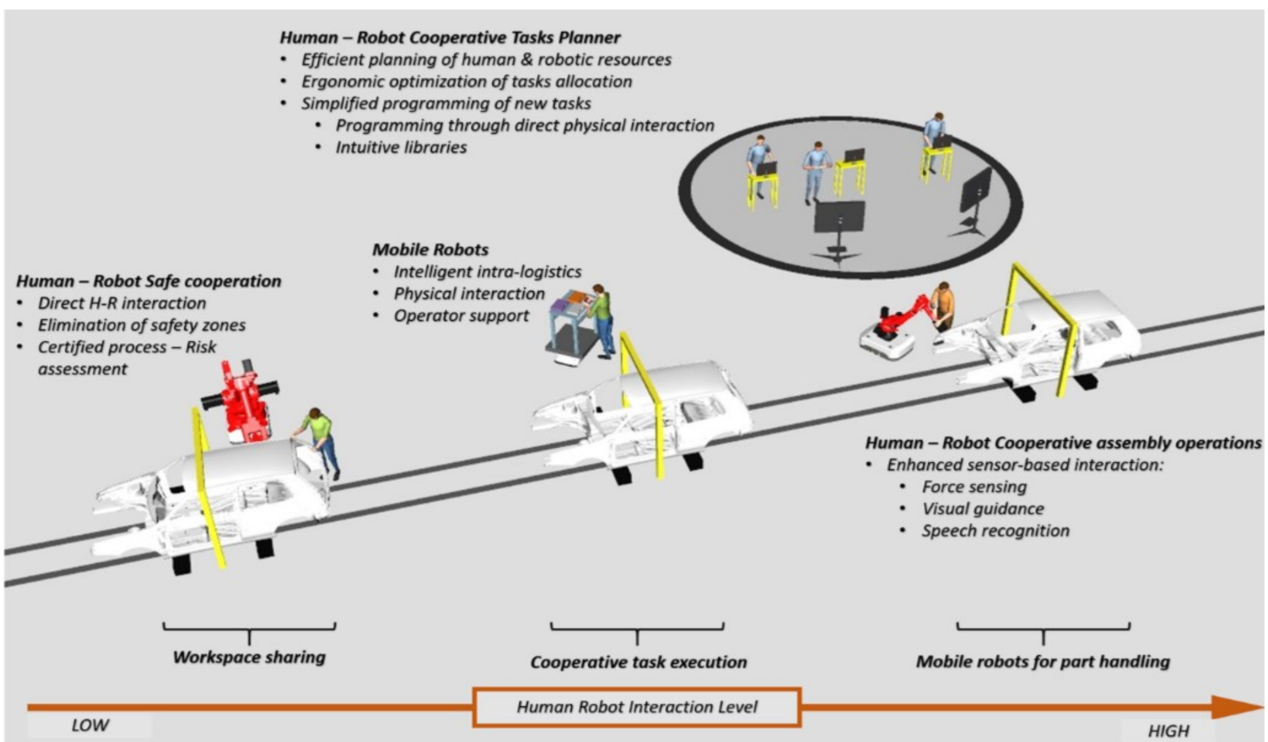

Figure 22. Hybrid Production Systems (Michalos et al. 2014)

The inclusion in the industry of more sophisticated robots invites the use of new AI techniques since more and more data is computed to obtain very precise results in the shortest possible time. Focusing on the dynamic task planning systems, which can derive critical productivity benefits flexible plan-based solutions can be a key enabling feature of HRC controllers where robot motions must be continuously adapted to the presence of humans, which act as uncontrollable "agents" in the environment. Moreover, the integration of Planning and Scheduling (P&S) technology with Knowledge Engineering solutions and, more specifically, with verification and validation techniques is a key element to synthesize safety critical systems in robotics (Orlandini et al., 2014). The aforementioned conditions synthesize the challenges which academia and research have been dealing with by developing several AI-enhanced solutions that will be analyzed in the following paragraphs. In more detail, the next paragraphs present applications of AI extracted from projects like Sherlock, Thomas, Odin, Remodel, Romoflex, among others, which have demonstrated how the industry can benefit from AI. The contents of the following paragraphs are the following:

1. Hierarchical knowledge modelling for robot programming, task & workspace planning
2. Intelligent ergonomics assessment for workstation layout design
3. AI for dynamic task and motion planning
4. AI for flexible and precise robotics
5. AI for dynamic operator support
6. AI-enhanced human-robot interaction
7. AI for predictive maintenance

3.1 Hierarchical knowledge modelling for robot programming, task & workspace planning

Decision-making in manufacturing systems aims to achieve performance requirements e.g. cycle times, costs, and so forth, by selecting values for particular values of decision-variables e.g. location of machinery, allocation of tasks, etc. Typically, the mapping of decision variables to the expected performance has been accomplished with techno-economical models, however with the introduction of new requirements such as the integration of various systems for production, the simplification of robot programming, and the increase in robots' accuracy the types of models is more and more extended (Chryssolouris, Alexopoulos & Arkouli, 2023).

For instance, semantic models have been used to facilitate the integration between various systems for production, coordination and interaction, and they are becoming more and more part of industrial solutions Semantic models, originally used for symbolic reasoning and descriptions of linked-data sets. Semantic knowledge modeling is a process of creating a computer interpretable model of knowledge or standard specifications about a kind of process and/or about a kind of product. The semantic models are expressed in a knowledge representation language or data structure that enables humans and automated software components to interpret the meaning of the data in a consistent manner. Knowledge models are used to guide the creation of a product. Also processes imply the use of semantic models, a process model is in fact a semantic description of how to go from one step in the process to another, involving an action on a particular product. Similarly, a knowledge model of an assembly physical object is a decomposition structure that specifies the components of the assembly and possible the sub-components of the components and its processes.

The effort to simplify robot programming and increase the intuitiveness in Human-Robot Interaction (HRI) has frequently stimulated research about representing human, robot, or shared human-robot activities. Task-oriented robot programming that focuses on 'what' is to be done, as opposed to the motion-oriented programming that focuses on 'how to be done' is deemed to be more aligned with the efforts for intuitive programming (Makris et al., 2014) as it can enable the development of interfaces that will assist humans to transfer high level commands to a sequence of robot motions and actions. In this view, methods for robot programming grounded on the hierarchical decomposition of complex activities into simpler ones concurrently with the definition the sequence of operations and the creation of robot libraries including simpler robot tasks have been suggested (Makris et al., 2014). For instance, the method Figure 23 is based on three modules for the programming of a dual arm robot: the robot language, the human intention recognition and the human language. The robot language involves the high layer robotic library for the bimanual tasks, e.g., BI-APPROACH, BI-INSERT, etc. to support the dual arm motion control. The human language includes all the sensors/interfaces and the selected methodology for interaction including gestures, voice commands and graphical user interfaces (GUIs). The arguments for each operation such as start and target robot position are defined from human interfaces, voice commands and gestures. The human intention recognition maps the recognized human gestures to robot language commands. The implementation of the approach was based on a service-oriented architecture developed in ROS realizing an assembly task coming from the automotive industry achieving important reduction of programming steps and thus, of the overall programming effort.

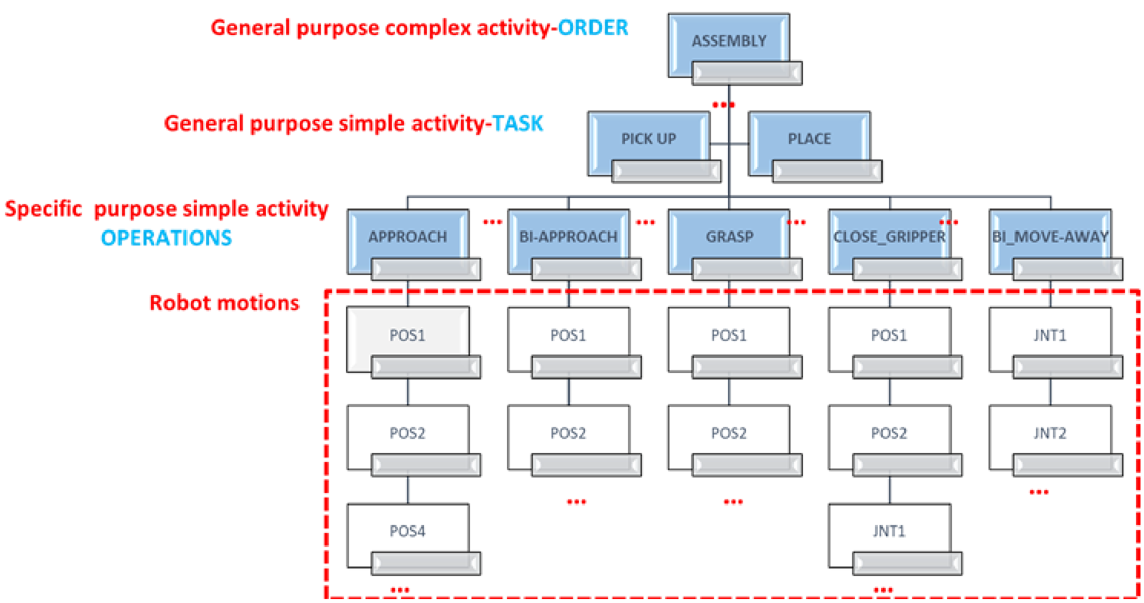

Figure 23. Robot process hierarchical modelling, (Makris et al., 2014)

The concurrent modelling of human and robot tasks together with the existing resources in a unified model have been proposed to support the Human Robot Collaborative (HRC) workplace design, as well as the automatic task allocation. Methodologies based on hierarchical models may address the workstation layout design problem but also the task allocation. The approach in Figure 24, firstly locates all the components and following maps tasks to resources using a smart decision-making framework (Tsarouchi et al., 2016). The evaluation of the alternative HRC workplace layouts is based on multiple criteria such as ergonomics, whereas the system has been integrated with a user interface into a 3D simulation tool and tested on an automotive industry case study. Reduced time for redesign and reconfiguration of workplaces and process plans was noted.

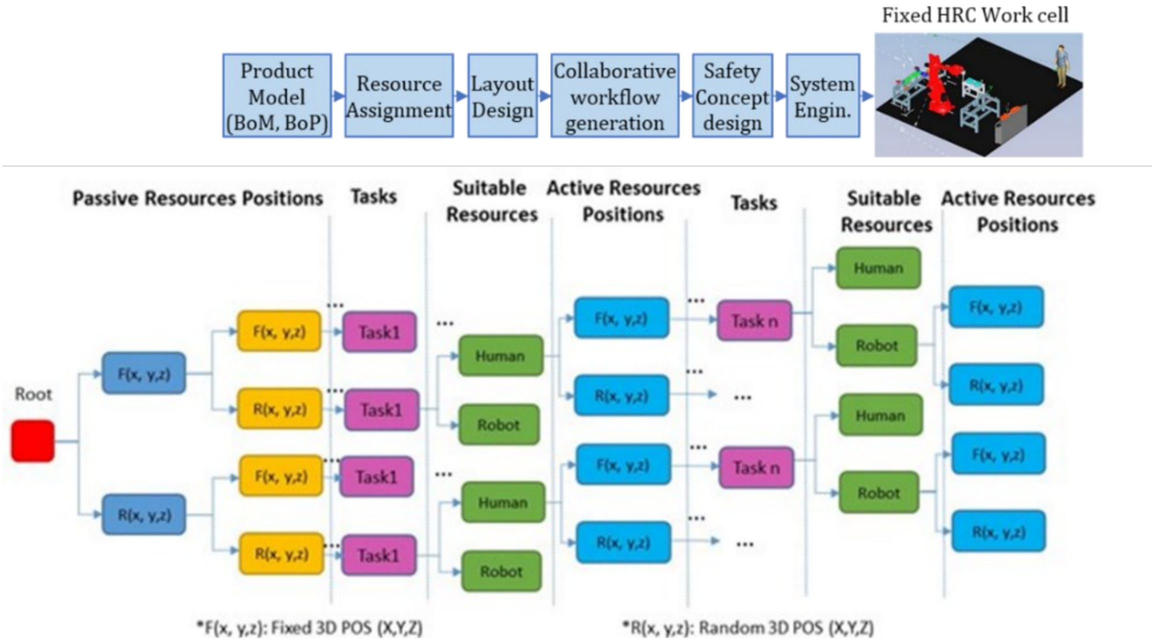

Figure 24. Workplace and resources hierarchical modelling, (Tsarouchi et al., 2016)

The design of automated cells currently requires considerable time and a working team of engineers, designers, system integrators, robot specialists, etc. The integration of rules and knowledge about cell design in AI-algorithms into the automated generation of good quality workstation designs in short time have attracted research interest. The prerequisite steps of such module should involve the modeling of the problem the definition of different criteria, (which are either calculated analytically or computationally), and then a set of algorithms, e.g. heuristics-based search algorithms (Tsarouchi et al., 2017), for generating design alternatives, before selecting the most appropriate one. The modeling of the system is typically performed by combining rational data, or data from different sources and their geometrical counterparts that enable to model, of the actual production system, as well as the kinematic and dynamic constraints. Popular criteria for the alternative selection may be the payload, reachability, dexterity, number of required resources for a task, etc. The impact of using such methods includes the efficient design of work cells with reduced space utilization, and optimized resource utilization. Furthermore, Kokotinis et al., 2023) have worked on the quantification of the quality of human-robot collaboration, which can significantly support the ranking of human-robot collaboration scenarios based on human-centric viewpoint.

3.2 Intelligent ergonomics assessment for workstation layout design

As workplace layout is closely related to the worker wellbeing, physical fatigue but also productivity, and production costs the investigation of the impact it has on human operators are gradually investigated to a greater extent. Until recently, workplace optimization has been based on observational methods and software simulations which may not be as insightful to prevent workstation layout redesigns and interventions when the actual setup is in-place. On the other hand, full size prototypes entail high costs and implementation time. An alternative which can significantly reduce costs for physical prototypes construction and workplace design, as well as prevent redesign iterations deriving from the operators' requirements and needs is the simulation in Virtual Environments with simultaneous data capturing.

Virtual Reality (VR) has been proposed for simulation of industrial operations and optimization of shop floors and workflow design (Rentzos et al., 2014). A review of the available methods together with a decision-support framework for the selection of the proper ergonomics evaluation method depending on the use case requirements has been presented (Arkouli, Michalos, and Makris, 2022) In this view, frameworks allowing inexpert users to create 1:1 replicas of industrial shop floors in an efficient manner, rapid modelling of tasks and actions for the preparation of Virtual Reality based assembly simulations (Dimitropoulos et al., 2020). The exploitation of VR simulation to analyse and enhance industrial workplaces by collecting more realistic data involving operators performing their actual task on a simulated environment is another area where researchers have focused (Michalos et al., 2018) to enable the tracking of (multiple) users virtually performing assembly tasks, with simultaneous visualization of KPIs (e.g. completion time, traveled distance, ergonomics) to support the relevant decision making.

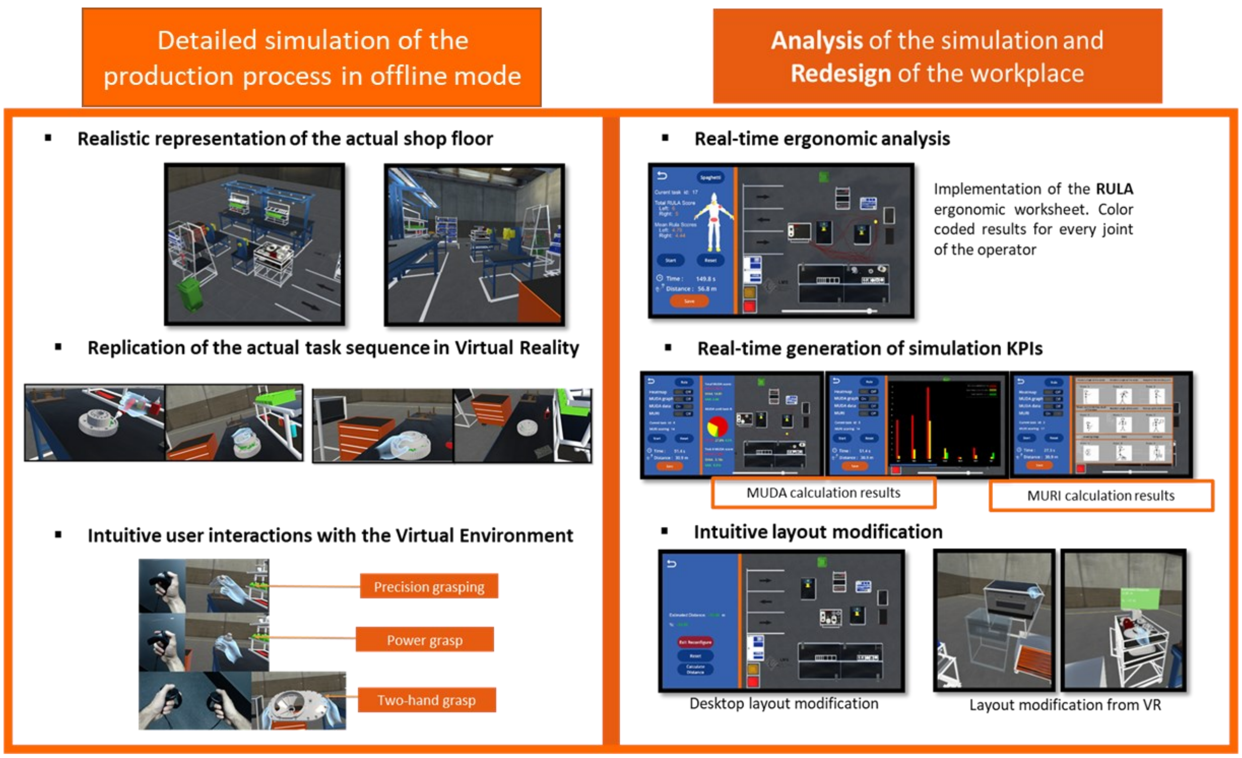

Figure 25. Human centred workspace design

3.3 AI for dynamic task and motion planning

Planning is another problem that requires notable effort and can be simplified with the use of AI based tools (Evangelou et al., 2021). A planning problem is typically modelled by identifying a set of relevant components whose temporal evolution must be controlled to obtain a desired behavior. Planning for real world problems with explicit temporal constraints is a challenging problem. Among different approaches, the use of flexible timelines in Planning and Scheduling P&S has been shown to be successful in a number of concrete applications, such as, for instance, autonomous space (Amedeo Cesta et al., 2007; Jónsson et al., 2000). Timeline-based planning has been introduced by Muscettola (N. Muscettola, 1994), under a modelling assumption inspired by classical control theory. Components represent logical or physical subsystems whose state may vary over time.

Since a decade, a research initiative has been started to investigate the possible integration of a timeline-based planning framework (Cesta et al., 2008) and validation and verification techniques based on Timed Game Automata (TGA) to automatically synthesize a robot controller that guarantees robustness and safety properties (Cesta et al., 2011; Orlandini et al., 2013). Unfortunately, these systems do not allow an explicit representation of uncontrollability features. Consequently, the resulting controllers are not endowed with the robustness needed to deal with the temporal uncertainty of HRC scenarios and controllability issues (Morris & Muscettola, 2005). These systems usually rely on replanning mechanisms that may however strongly penalize the production performance. The execution of a flexible plan is usually under the responsibility of an executive system that forces value transitions over the timelines dispatching commands to the concrete system, while continuously accepting feedback and, thus, monitoring plan execution. In such cases, the execution time of controllable tasks should be chosen so that they can face uncontrollable events. This is known as the controllability problem (Vidal & Fargier, 1999).

In (Cesta et al., 2016) the general pursued approach is presented aiming at realizing controllers capable to dynamically coordinate tasks according to the behaviors of human workers. Umbrico et al. presented a task planning and execution framework (PLATINUm) and its integration with a Knowledge Engineering solution describing its deployment in safe and effective solutions for manufacturing HRC scenarios (Umbrico et al., 2018). PLATINUm is a timeline-based planning system capable of supporting flexible temporal planning and execution with uncertainty. PLATINUm has been used to introduce an innovative integrated motion planning and scheduling methodology that (i) provides a set of robot trajectories for each task as well as an interval on the robot execution time for each trajectory and (ii) optimizes, at relevant time steps, a task plan, minimizing the cycle time through trajectory selection, task sequence and task allocation (Pellegrinelli et al., 2017). PLATINUm has been used to combine task and motion planning efficiently in HRC pursuing a control-based approach based on two layers, i.e., task planning and action planning. Each layer reasons at a different level of abstraction: task planning considers high-level operations without considering their motion properties; action planning optimizes the execution of high-level operations based on current human state and geometric reasoning. Also, connections with ontologies and semantic technologies are provided to demonstrate how abstractions and meta-reasoning can bring additional advantages in terms of adaptability and effectiveness in dealing with uncertainty (Borgo et al., 2016; Umbrico et al., 2020).

In the perspective of increasing the responsiveness of production, collaborative Mobile Robots have been put on the spotlight to endow dynamic re-organization of the work in production systems. Mobile robots however call for dynamic generation and evaluation of the mobile robots' task sequences, as well as the respective motions. The planning and optimization of the mobile robot paths has been addressed with several approaches illustrated in Figure 26 breakdown into sub-problems. Two main categories can be distinguished in the highest level i) global and ii) local planning. Each one of the two path planning modes requires modeling, optimization criteria, and searching. Especially the searching part can be enhanced by the implementation of AI-based applications such as the Artificial potential field. Robot abilities that are addressed include autonomous navigation (optimization of 2D trajectory) and manipulation (optimization of 3D trajectories). Including dynamic obstacle avoidance and online re-planning. Applications that require path planning in manufacturing include but are not limited to the following: delivery, autonomous car, logistics, fleet management of AGV and AMR to achieve better cycle times through offline simulations and online optimization calculations.

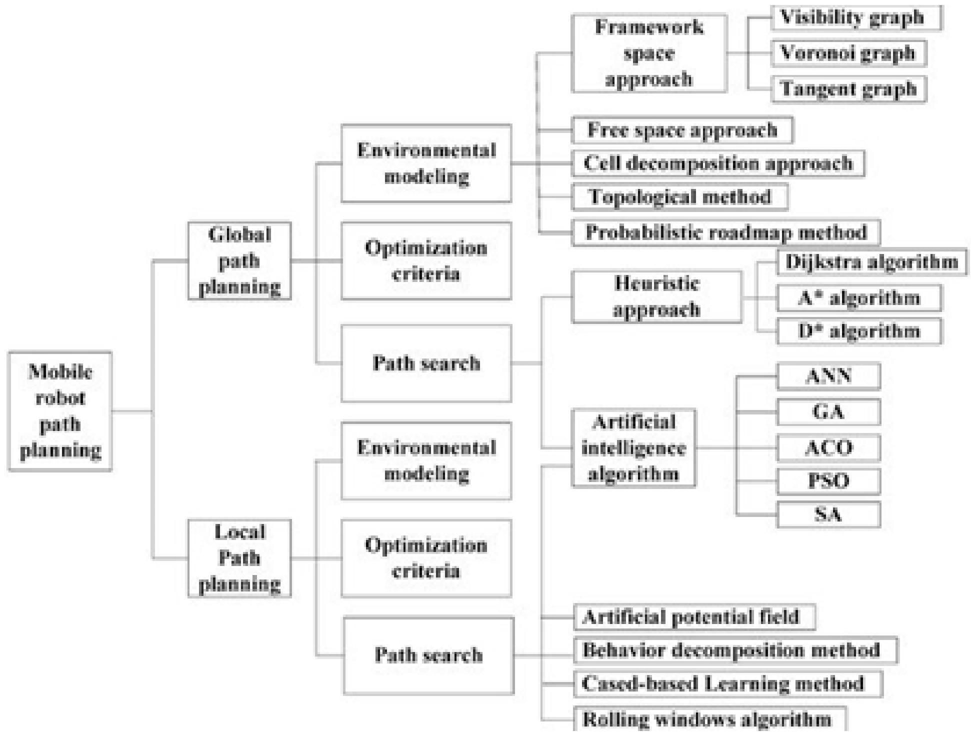

Figure 26. Mobile robots path planning problem analysis

Approaches on planning for hybrid production model considering not only the robot actions but also the tasks and resources have been proposed. In some approaches hierarchical models of the tasks and resources are used to add context for decision-making and in scope of ensuring that the context is always relevant, the digital twin concept has been used (Kousi et al. 2019). In the application depicted in (Figure 27) the digital model of the workstation is updated with data coming from the field, whereas the target of the proposed digital twin-based approach is to enable decision-makers to acquire context on the current shopfloor status and have up-to-date information about the actual production process.

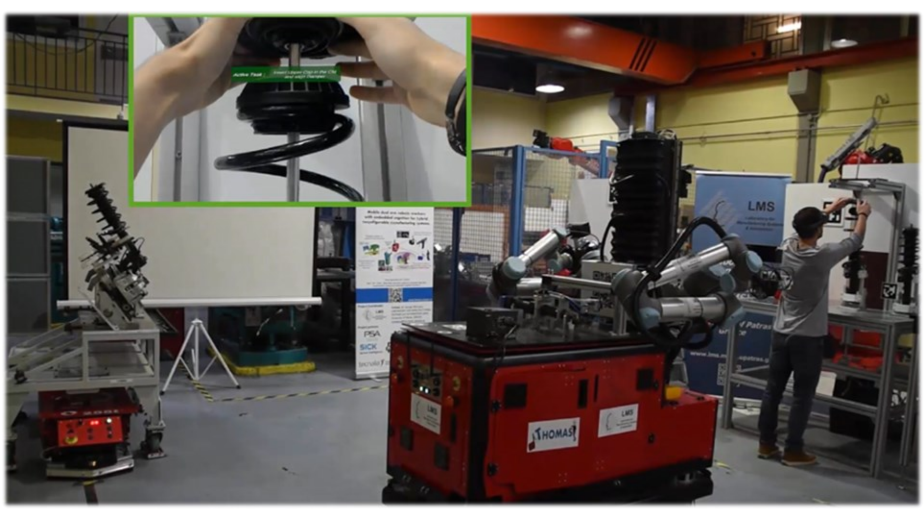

Figure 27. Scheduling and motion planning of mobile robots

This is achieved by firstly realizing the virtual twin of the system, i.e., modeling the parameters of the production system at different levels including assembly process, production station, and line level. The models capture both geometrical information and semantics.

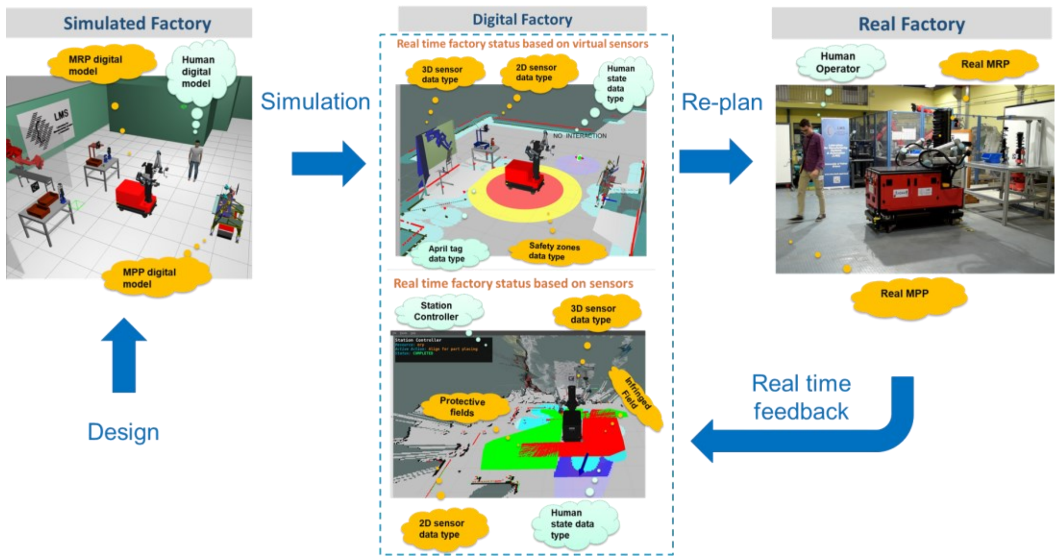

Figure 28. Digital Twins for Human-centric reconfigurable manufacturing lines, (Kousi et al., 2021).

The models can be used together with an AI logic to generate alternative configurations of the production systems. In particular, for the implementation of (Kousi et al., 2021) the suggested digital world model infrastructure involves three main functionalities: 1) Virtual representation of the shopfloor, synthesizing multiple sensor data and CAD models. The digital shopfloor is rendered in the 3D environment benefiting from the capabilities provided by Robot Operating System (ROS) framework, 2) Semantic representation of the world through the implementation of a unified data model for the representation of the geometrical and the workload state, and 3) Dynamic update of the digital twin based on real time sensor and resource data coming from the physical shopfloor. The communication and integration layer among the physical and the virtual agents is implemented on top of the ROS framework (Kousi et al., 2021). The developed infrastructure has been applied to an industrial case study coming from the automotive industry focusing on a car’s front axle assembly. Nevertheless, it is designed to be generic enough to accommodate cases. The impact that was achieved by implementing this approach involved reduced time to adapt the production system and respond to unforeseen situations (Kousi et al., 2019).

3.4 AI for flexible and precise robotics

The manipulation of complex parts by industrial robots is a challenging application due to the uncertainty of the parts’ positioning, the distribution of the part’s weight, as well as the gripper’s grasping instability that has been favored by the use of vision systems. The instability is a result of non-symmetrical and complex geometries that may result in a slightly variable orientation of the part after being grasped, which is outside the handling/assembly process tolerance. In order to address this challenge, machine learning methods can be employed to recognize the parts and estimate their position and orientation after they have been grasped. The implementation of such approaches can increase the number of successful operations, the tolerance to the object’s initial positioning, but also to the part’s compliance, and the object’s geometrical complexity (Aivaliotis et al., 2017).

The growth of industrial sectors (automotive, aeronautics, clothing industry, etc.), whose processes involve deformable parts such as textiles and composites, has stimulated the automation of the manipulation and assembly of deformable parts. This research area up until recently was not very active due to the challenges related to flexible material deformability that are enhanced by the limitations of robot dexterity and perception during the deformable parts handling. Some solutions have though been presented.

The robot manipulation and assembly of linear non-rigid components including the safe flexible material supply, part detection and grasping (Figure 29) and cross section recognition (in case of non-symmetrical parts) was addressed in (Andronas et al., 2022). Also, the identification of the most convenient grasping point, which is troubling due to the stochastic positioning and configuration of the objects, it is described by Sardelis et al. (2020).

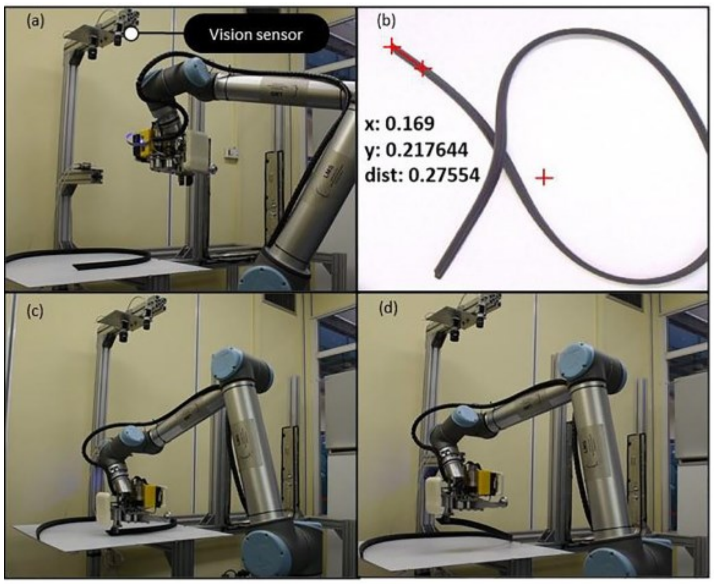

Figure 29. Grasping of a randomly positioned flexible part: (a) detection, (b) detection results (c) edge localization (d) part grasping (Andronas et al., 2022).

Human-robot or multi-robot fabric co-manipulation has also been addressed. A model-based closed-loop control framework for seamless co-manipulation has been developed to exploit the potentials of HRC in this application field in (Andronas et al., 2021). A mass-spring model is used for simulating ply distortion and generating optimal grasping points' spatial localization. The model is enriched with real-time operator's handling actions, as captured from the implemented perception system. The proposed sensor and model-based controlling framework incorporates robot motion planners for operator support, through non-rigid object co-manipulation, or synchronization of cooperative robots within fully automated tasks. An experimental setup was used for validating system's handling cognition during collaborative manipulation showing that there is potential for important improvements in the quality consistence, the ergonomics of the operator, but also the resilience into pandemics (Andronas et al., 2021).

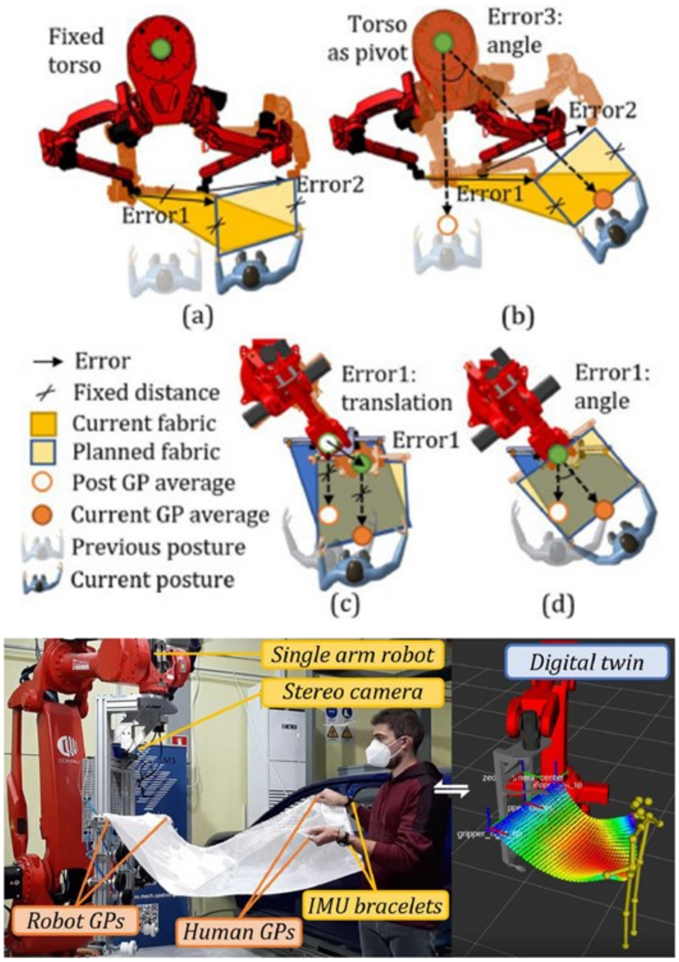

Figure 30. Co-manipulation of flexible parts, (Makris et al., 2022)

Other researchers focused on increasing the accuracy of machine equipment modelling in order improve their accuracy, energy efficiency, and so forth. Nowadays, robot manipulators are far from the traditionally heavy and stiff structures, which in turn leads to less accurate positioning of the robot end effector due to the flexibility of robots' links and gearboxes complementary to the friction phenomena that are present in the motor's gear box. To this end, Aivaliotis et al. proposed an easy-to-use method for the identification of an industrial robot's dynamic parameters based on physics-based simulation models. Robot motion data from both the digital and the physical robot together with an intelligent algorithm were employed to estimate the robot's dynamic parameters and eventually adjust the control of the robot motion to improve accuracy (Aivaliotis et al., 2020).

3.5 AI for dynamic operator support

AI-based computer vision modules usually include a set of tools and methods that allow obtaining, processing, and analyzing images of the real world so that they can be processed by a computer. Common applications in the manufacturing field are: inspection and recognition of failures, quality control, perception of the environment, detection and tracking. Apart from that, they can be used to provide support to human operators. In this context, systems to detect errors as they are being performed, and prevent their propagation to the upcoming production steps are required. An object and human hands detection vision system in combination with intention identification based on Convolutional Neural Networks (CNNs) are proposed to automatically monitor the execution of human-based assembly operations. The error handling is addressed by the provision of dynamic step-by-step instructions that are provided to the operators via multi-modal user interfaces (Andrianakos et al., 2020).

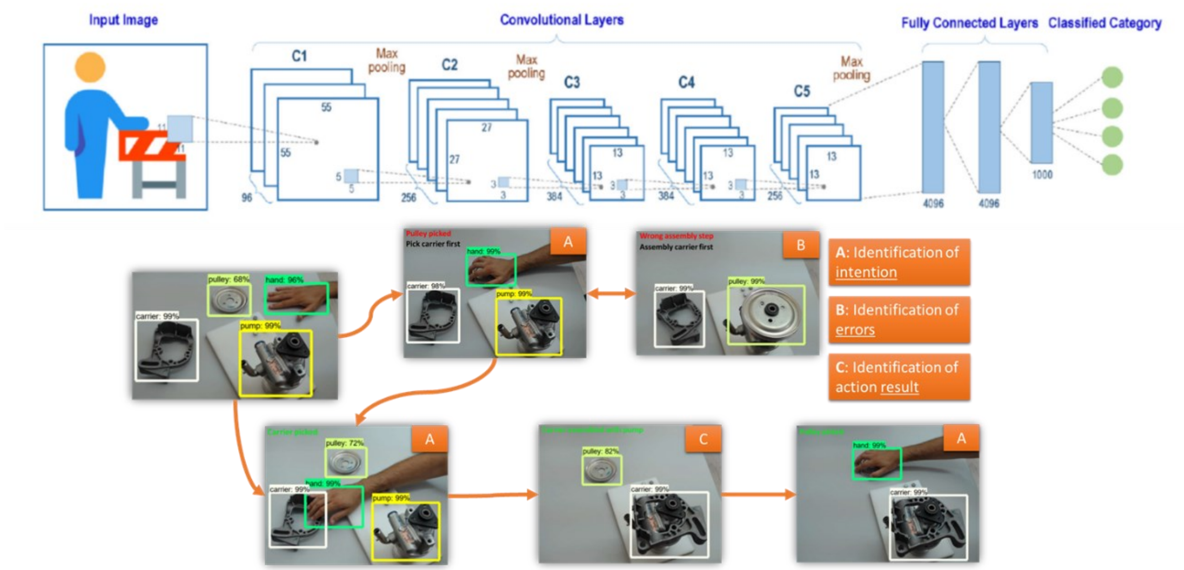

Figure 31. AI-empowered process surveillance and dynamic step-by-step instructions, (Andrianakos et al., 2020)

ViTroVo is another similar solution involving an artificial intelligence framework capable of (1) autonomously building a graph of assembly steps via trial-and-error (in vitro Assembly Search) and (2) presenting relevant instructions to a human operator and, by autonomously detecting her progress and affective state, adapting accordingly (in vivo Adaptive Operator Guidance). The power of ViTroVo resides in its versatile way to manipulate a given product's component Augmented Computer Aided Design (CAD+) models throughout the whole assembly task (Grappiolo et al. 2021).

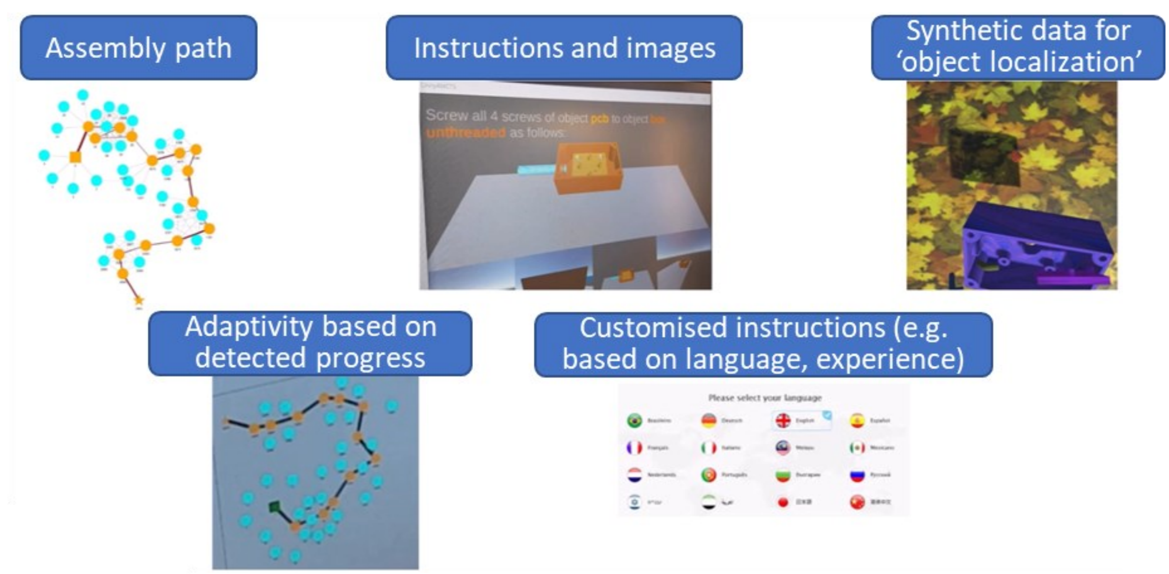

Figure 32. Artificial Intelligence creates assembly instructions from CAD, (Grappiolo et al. 2021)

3.6 AI-enhanced human-robot interaction

Research on human robot interaction so far has addressed the improvement of the collaboration between humans and robots, mainly focusing on task sharing and allocation, safety, awareness, and cognitive support in form of Augmented Reality based instructions. For instance, the Robot Companion platform (Gosselin et al, 2022) integrates various technological bricks enabling to meet the needs of factories of the future in an iterative and agile way (Figure 33). The main components (apart mechatronics and embedded systems) are digital twin, vision sensors and algorithms (recognition and localization of objects), environment monitoring (analysis of the presence and activity of the operator), orchestration and task-planning (planning and execution of robotic actions), robot control, and communication protocols between the different components of the robot and between the robot and its environment. Gesture recognition and analysis of human-robot interaction as well as natural language interactions are also expected in the longer term. Several systems with similar objectives have been developed in different laboratories or by industrial companies over the last decades (MIT, Willow Garage, Halodi Robotics, University of Washington, Waseda University, DLR, TUM, KIT, Toyota Research Institute, Fetch Robotics, Robotnik, Pal Robotics,…). However, their use is often limited to demonstrations in laboratory environments, home or logistics. Industrial Robot Companions (e.g. Kawada, Epson) remain confidential and are mainly used as a showcase for their manufacturers. Only collaborative robots (Universal Robots, Kuka, ABB) are more widely distributed, but they do not have all the characteristics of a Robot Companion. Indeed, the vision defined above can only be realized if all the technologies used to make robots more efficient, more interactive, more intelligent, more communicative and safer reach a sufficient level of performance and maturity.

The demonstrator in Figure 34 addresses the assembly of randomly deposited mechanical parts on a fixed base and presents various challenges, in particular for vision (small, similar and shiny parts), capture and assembly (smooth parts, of very variable sizes, insertions with very little play, screwing) and integration of various technologies. A new demonstrator with two arms is being built to perform tasks more smoothly and quickly. The ambition is also for the robot(s) to be able to handle cases where not all objects are visible or reachable at the beginning, forcing the system to have dynamic adaptation capabilities with re-planning during execution to be able to adapt to unexpected situations. The medium-term objective is to have a demonstrator capable of learning and performing new tasks and in the longer term to be able to perform different assemblies on the fly with full autonomy and mobility.

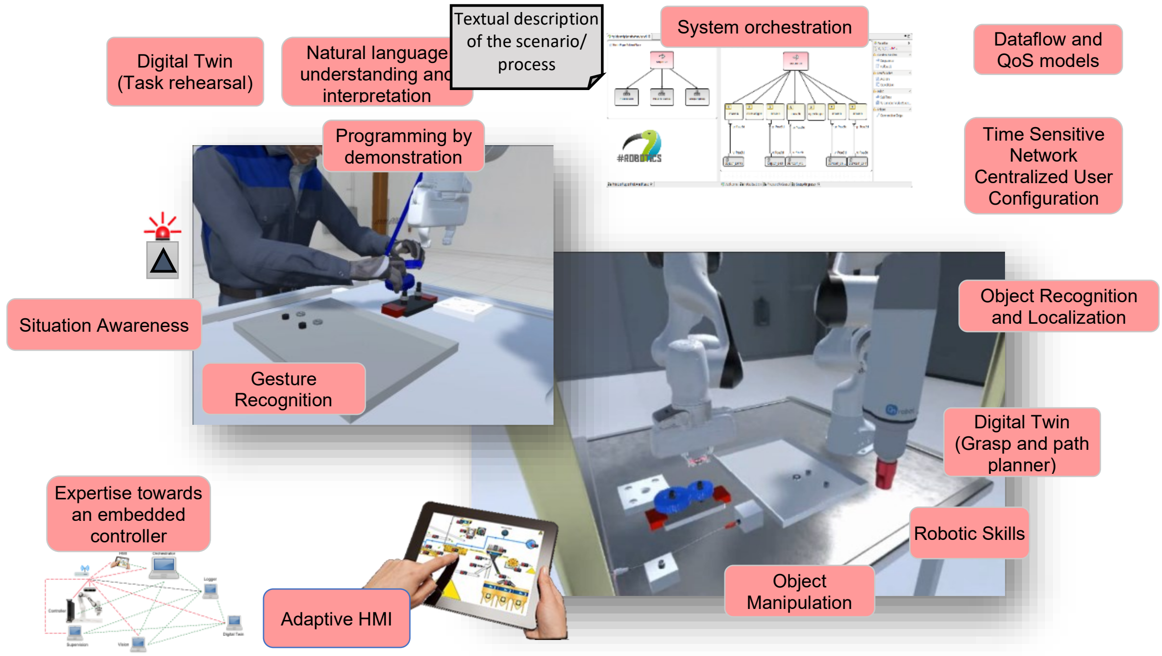

Figure 33.Overview of the main functionalities of the Robot Companion

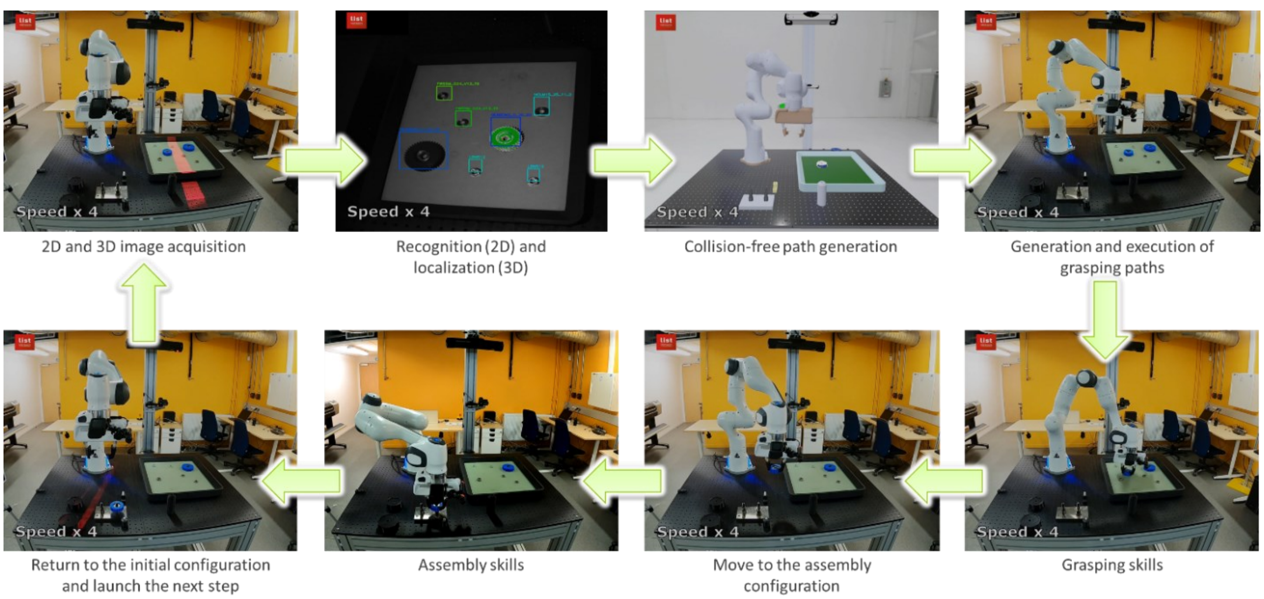

Figure 34. Assembly of randomly deposited mechanical parts using AI-based vision capabilities

Apart from light-weight collaborative robots, researchers has also worked on enabling high payload collaborative robots to work side-by-side with humans. This in turn required dynamically reconfigurable safety monitoring systems and smart Human Robot interfaces allowing the seamless integration of operators and robots in a common workflow has been presented in (Dimitropoulos et al., 2020). Among others, the presented solution can support a variety of hardware to easily fit in various industrial scenarios, and it has been tested in two case studies inspired by the elevators production and industrial modules production fields. The results of the testing and validation procedure indicate reductions in cycle time, operator idle times, but also improved operator satisfaction, and operator ergonomics (Dimitropoulos et al., 2021).

Figure 35. AI-enhanced operator support & robot adaptability to improve user experience, (Dimitropoulos 2021)

3.7 AI for predictive maintenance

The maintenance of machining processes is one of the most studied topics in manufacturing industry, due to its relevance for the process behavior and the economic impact on the production plans. Two different maintenance methods are applied in most of the industries; On the one hand, preventive maintenance, based on the theoretical life of the tool. On the other hand, predictive maintenance uses strategies such as inferring the remaining useful life (RUL) of the tool, which mostly depends on the wear measurements (Cerquitelli et al., 2021a, Cerquitelli et al., 2021b). It is critically important to assess the RUL of an asset while in use since it has impacts on the planning of maintenance activities, spare parts provision, operational performance, and the profitability of the owner of an asset. The objective of predictive maintenance is to predict when equipment failure may occur and to prevent a failure by performing maintenance. Ideally, this approach enables the system to have the lowest possible maintenance frequency.

The field of prognostic maintenance (Giordano et al., 2021) aims at predicting the remaining time for a system or component to continue being used under the desired performance. This time is usually named as Remaining Useful Life (RUL). In order to enable such approaches in a cyber-physical production system, a deep learning algorithm is used (Bampoula et al., 2021) - Figure 36, allowing for maintenance activities to be planned according to the actual operational status of the hot rolling mill machine and not in advance. The rolling mill is composed of two rolling cylinders, rotating using torque motors. The lower rolling cylinder has a fixed position and only the upper can move linearly (vertical) The segments have a wear-resistant coating that degrades over time. The machine has mounted sensors, measuring cylinder hydraulic forces and segment surface temperatures. The approach aims on enabling Predictive Maintenance (PdM) for the coating segments of a hot rolling mill machine, through estimating in real-time their RUL. Monitoring the wear stage of machine components can lead to improved scheduling of maintenance activities. An autoencoder-based methodology is employed for classifying real-world machine and sensor data, into a set of condition-related labels. Real-world data collected from manufacturing operations are used for training and testing a prototype implementation of Long Short-Term Memory autoencoders for estimating the remaining useful life of the monitored equipment.

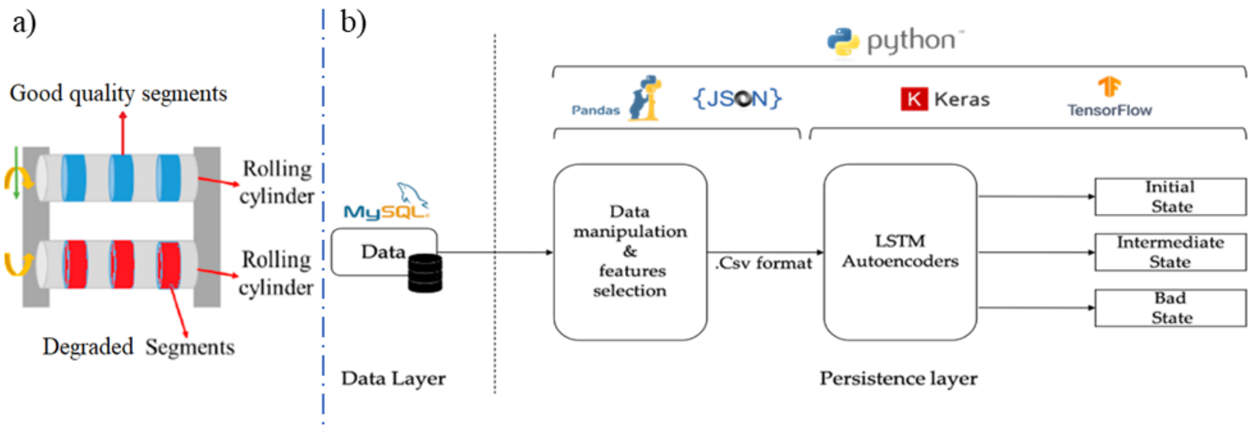

Figure 36. a) Rolling mill with degraded (red) coatings, b) LSTM-autoencoder implementation, (Bampoula et al., 2021)

Other approaches involve correlation analysis and recurrent Neural Networks for machine failure forecasting. In this case, having the operational parameters of the positive displacement pump machines (e.g.: temperature, humidity, voltage, torque, force, etc.), and some Operation & Maintenance (O&M) records that indicate the date when the machines had some kind of abnormal behaviour, the AI-based approach would consist of correlating both sources of information to produce a health status of the machines and study how it evolves over time in a prognosis framework. To do so, a semisupervised self-learning method is first applied to the O&M data since they are imprecisely categorized and have unreliable dates. Then an anomaly score is defined and a recurrent neural network is fit to it in order to forecast when a machine failure is going to occur given the previous trend.

Deep Neural Networks have been employed for anomaly detection and identification of underperformance Figure 37. Given the vibrations of the blowers and pumps acquired by accelerometers and the operational context of the assets (e.g.: damper opening degree, composition of the combustion gases, etc.), a deep neural network-based model for anomaly detection is first learned. Then an adaptive strategy based on a context drift detector is deployed to automatically adapt the deep model to changing and dynamic production conditions, and thus detecting when the performance of the assets is not optimal given the current operational context.

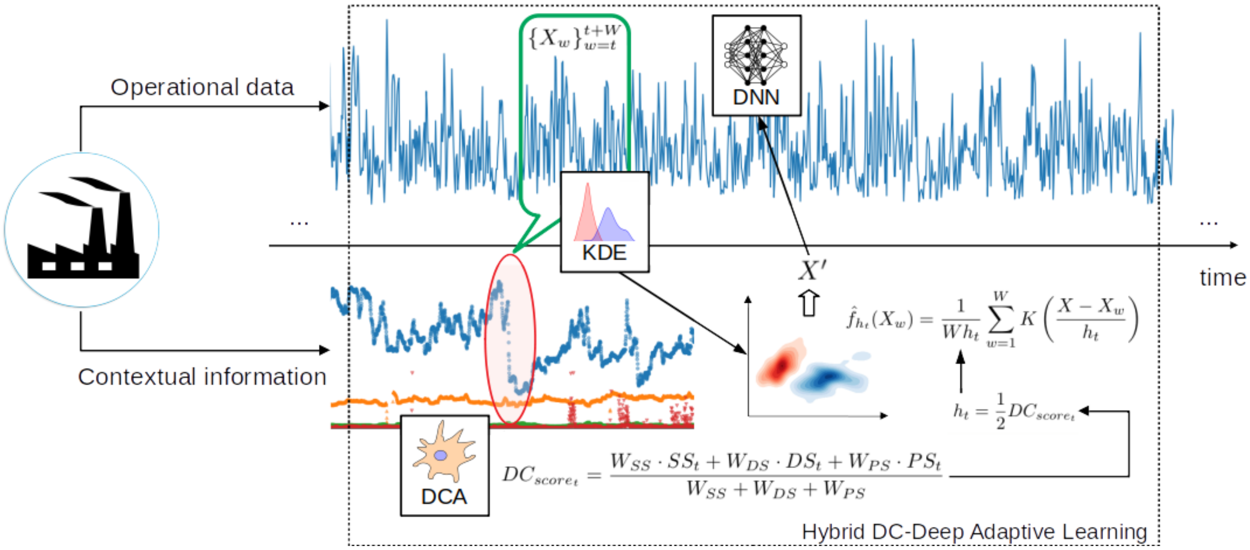

Figure 37. Deep Neural Networks for anomaly detection and identification of underperformance

Research on predictive maintenance so far has involved mainly data-driven prognostic techniques for machinery equipment individual components. Simulation capabilities can address the lack of historical data but also any challenges that are induced by the intricate design of industrial machines, e.g. robots that are frequently reported. In this perspective, a generic framework for the enhancement of advanced physics-based models with degradation curves has been proposed (Aivaliotis, Georgoulias, et al., 2019). The creation of a robot's simulation model can play an important role in the accuracy of the simulation results (Arkouli, Aivaliotis, Makris, 2021). Moreover, due to the variations of the behaviour of the machinery equipment that stem from their use and the relevant fatigue invite for the continuous monitoring and update of the digital model parameters, which can be based on data and information extracted from degradation curves of the robot's components. The health status of the robot can be monitored using a Digital Twin based approach that ensures the convergence of the simulated to the actual robot behaviour (Aivaliotis et al. 2023). The simulation can estimate the future behaviour of the robot and predict the quality of the products to be produced, as well as to estimate the robot's Remaining Useful Life. The proposed approach is applied in a case study coming from the white goods industry, where it is investigated whether the robot will experience some failure within a predefined timeframe. The expected outcomes involve improved resource availability, product quality, etc. (Aivaliotis et al., 2021).

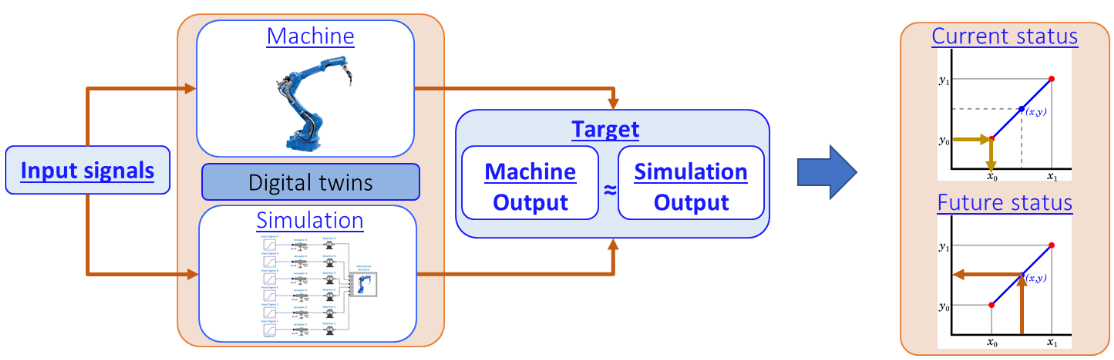

Figure 38. RUL prediction enabled by physics based models enhanced with degradation curves, (Aivaliotis et al., 2021)

3.8 Consolidation of AI application at the Machine and Station level

Industry and academia have been working on solutions to increase productivity fulfill the market demand for highly customized products. Although those have been ongoing research issues for some decades and many of the proposed solutions over the years have managed to improve the productivity and flexibility of factories, it seems that more effort is needed towards reducing integration costs, improve agility, and cover the requirements for an increased level of qualification and skills of operators. As an example, robotics, which has been widely deployed in industry over the last decades, is still often restricted to fully automated mass production applications that justify the implementation of perfectly controlled and monitored dedicated environments, with integration costs representing up to 70 to 80% of the cost of the production cell and development times that can range from a few days to several months.

This has motivated the integration of AI techniques in manufacturing applications. There have been several calls for European projects where project proposals are presented that include different AI techniques. Thanks to these calls, AI techniques are increasingly sophisticated and with greater applicability in industrial processes. For logistics tasks for example, within its great breadth and diversity, the inclusion of AI has helped a great deal. Intelligent trajectory planning, dynamic obstacle avoidance, large fleet management of AGV and AMR to achieve better cycle times through offline simulations and online optimization calculations.

AI for workstation layout, task allocation, and dynamic planning have dealt with fast reconfigurations, optimized performance, reduction of idle times, and dealing with unforeseen events. These items have been addressed combining the benefits of simulation and data-driven approaches, for the generation of alternatives while search-based intelligent algorithms using heuristics have provided promising solutions. Mixed Reality tools, further increase the information content that is available for decision-making by introducing human factors in the design loop, e.g., by enabling to measure the physical effort that is required for a specific task. As for the Digital Twin concept, it has been frequently employed to improve the quality of the decision-making by providing continuous contextual information on the actual shopfloor condition, including the availability of resources, space, and materials.

AI is also linked to the enabling of a number of robot skills that allowed to automate several processes, such as the manipulation of deformable parts, that would otherwise remain strictly manual. Vision systems allow to adjust the robot behaviour based on the status of its surroundings not only to prevent collisions, but also to guarantee stable processing/manipulation of parts. Human-Robot Collaboration/Interaction, broadens the range of applications that may benefit from automation. In this context, AI is responsible to endow the robot to perceive the status of the operator and then automatically adjust its behaviour in order to promote a safe but at the same time comfortable interaction/collaboration with the operator by respecting its needs and preferences. The needs may refer to the physical effort that is required by the operator (e.g. selection of robot trajectory so that the operator avoids the assumption of uncomfortable postures when processing a part that is held by the robot), the operators feelings concerning any stress that might be introduced by the motion profile of the robot (motion speed, and acceleration), as well as the effort and expertise that is needed to program the robot. Additionally, there is a growing demand comprehensible by the human's models that are used for decision-making, especially when it comes to critical applications, such as safety in human-robot collaboration. This item is addressed by the research field of explainable AI (XAI).

Besides robots, AI has also enriched the capabilities of humans by providing the right information when needed, e.g., surveillance of manual assembly for the detection of errors and provision of step-by-step instructions for error handling. Finally, AI can act enabling to predict the status of the machines or detect anomalies in the machinery equipment operation. CNNs seem to be a part of the majority of the approaches that have been presented so far. On the other hand, physics-based simulations may offer additional insight on the machineries internal condition, which stimulates efforts towards hybrid models.

Figure 39 depicts the implemented AI solutions so far, as well as the achieved impact together with the expected results for the years to come. Regarding the efficiency of hybrid productions systems, theoretical and experimental work is still needed to improve the performance and stability of the control of such increasingly complex systems. This work is expected within the next 5-10 years and can exploit model- or data-driven approaches, capitalizing on the most recent advances in artificial intelligence as proposed for example by Alphabet/Intrinsic, and taking into account both the robot and perirobotic components such as sensors, environmental perception and scanning functions, and dedicated effectors (e.g. inspection, NDT, assembly, welding, ...).

Performance improvement also requires working on software and embedded systems, with the objective of minimizing the sensor latencies and/or optimizing the execution times, energy efficiency or even the size (and therefore weight and consumption) of the embedded electronics. Example critical functions that can benefit from this work cover the data fusion of heterogeneous sensors to monitor the system's and environment's state, the acceleration of vision/recognition/localization functions thanks to the optimization of image processing, or the acceleration of collision-free motion/path planning as proposed by RealTime Robotics who implemented Georgia Tech algorithms on FPGAs with a 100x gain. These developments are the basic components allowing the development of advanced robotic functions (mobility, gripping, bi-manual handling, man-robot collaboration, etc.), themselves at the heart of task or mission planning functions that can benefit from the digital twin of the robot(s) and their environment.

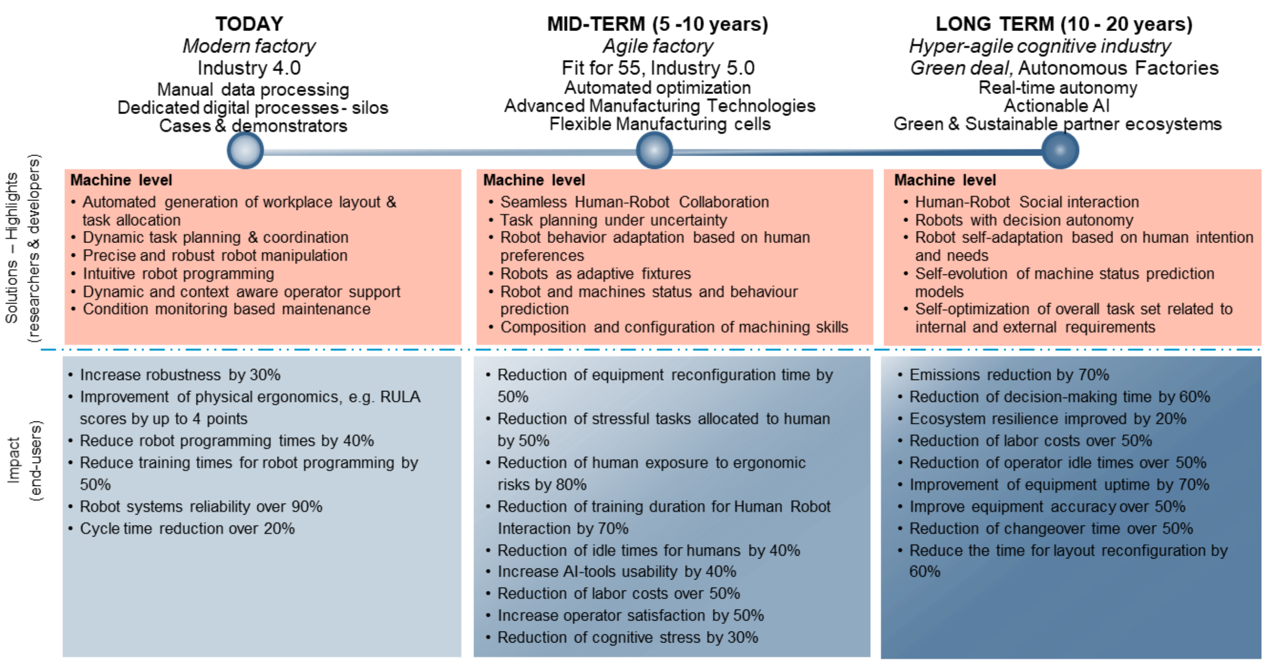

Figure 39. Current status and Future Vision for the adoption of AI at the Manufacturing Workstation level

The notions of interoperability, safety and security (physical but also cyber) are of course also central to hybrid production systems. Previous research indicates bottlenecks from the interaction of the operators with such supportive systems. The cause for these bottlenecks is the fact that both the direct interaction approaches (use of push buttons) or indirect-gesture based interaction require operators to constantly occupy their hands performing the relevant button presses or gestures (Dimitropoulos et al., 2020). Moreover, a great number of the proposed approaches are hardware dependent and need a lot of customization before being integrated with the rest of the hybrid system's components. Furthermore, it is for example extremely difficult to certify equipment at the hardware and software level, which can exclude some technologies. Demonstrating compliance with standards can therefore become crucial for the implementation of the technology. To enable early assessment of concerns such as performance, safety, security, reliability, etc., advanced software architecture design tools will be needed. These next generation systems engineering tools will be central for reducing design iterations and costly and time-consuming design cycles. These tools are also crucial for the development of interoperable solutions that allow such robots to be easily adapted to new tasks and environments, e.g. by communicating with other sensors (e.g. surveillance camera) and equipment in the plant. This requires efficient and secured communication capabilities, with dynamic safety and security features able to adapt to changing configurations and environments. These elements are central to the development of intelligent and trusted collaboration and cooperation functions, whether between several robots, between the robot(s) and their environment, or between the robot(s) and human operators.

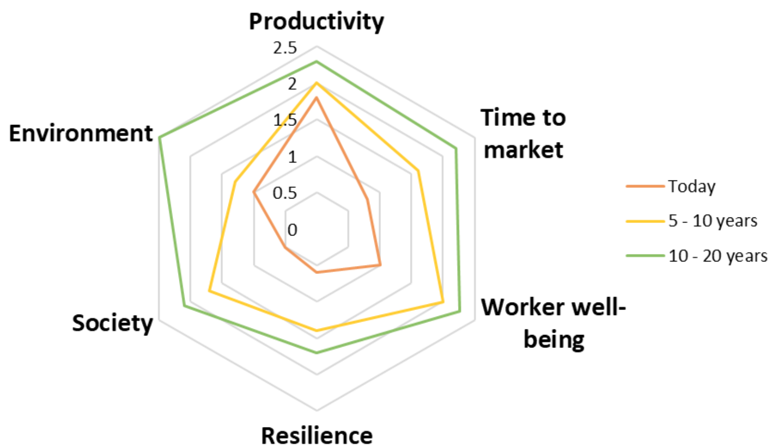

Figure 40. Degree of vision achievement

The long-term future involves the improvement of the intelligence of collaborative that will be capable of learning from themselves (e.g. deep reinforcement learning). In this context, the coupling of robots (and their environment) to their digital twin could allow the development of hybrid approaches combining learning in simulation and in the real world (e.g. Sim2real approach). We can also rely on the operators to teach the robots, with the possibility of exploiting very intuitive and natural interaction paradigms to manipulate the robots and show them the actions to be performed without any knowledge of programming or robotics (programming by demonstration, by imitation). Federated learning or symbolic AI are also enablers to give the robot better reasoning and reaction capabilities. The co-existence of robots and human operators in future factories also requires robots that are sufficiently expressive for operators to immediately understand what they are doing and to be able to work with confidence at their contact or in their proximity. Intuitive multimodal HMIs (e.g. gesture, touch, speech, vision) are also required for natural and efficient interactions.

Additionally, AI solutions respecting the existing standards make it possible to envisage systems easier to integrate into existing legacy environments ('plug and produce' concept) in the long-term future. However, it should be taken into account that standardization has not equally progressed in all the industrial sectors, for instance e.g., OPC-UA has been proposed for the automotive industry, while other domains (e.g. micro-electronics, food industry) are currently less structured and still use proprietary solutions. In addition, challenges remain in implementing modular and interoperable software architectures and solutions that guarantee the safety (compliance with current safety regulations, e.g. 15066) and cybersecurity of machinery equipment, which requires, in particular, the certification of the codes of the various components.

Maintaining and even relocating factories in Europe requires investing in manufacturing tools that are more efficient in order to guarantee the European competitiveness, more agile to adapt to a growing demand for customized and personalized products, and more responsible, keeping the human operators in the heart of factories. These challenges require the development of a whole new generation of plug-and-produce robots, i.e., very easy to install and use, making it possible to multiply the capacities of human operators by physically assisting them, by helping them to work more efficiently, or by performing part of their work autonomously, after learning from them.

4 AI at the System level

It has been observed that there is no commonly agreed definition of manufacturing systems level, as usually the definitions given by researchers or people in the industry differ. In this work, with manufacturing systems, a combination of machines, cells, intra-logistics devices, and other peripheral devices used on the factory floor as well as the relevant software is assumed. Moreover, the value chain of manufacturing systems including logistics is being considered under this hierarchical level. At this level, the complexity and interrelations among the entities increases, the volume of data also increases as it aggregates data from lower levels, and uncertainty, non-linearity, and stochasticity also increase. All these inherited attributes make transparency, predictability, and adaptability more challenging tasks for AI. However, at the same time as uncertainty and stochasticity increase, the need for accuracy of the models' results decreases, at least compared to the AI models in the lower hierarchical levels, and usually there are longer time frames available for decision making. The challenges in the industry at the system level mainly concern process efficiency and energy consumption maintaining the quality of the final product. Moreover, important challenges are the optimization of the available space while ensuring that all the necessary elements are included in the layout design and the workspace is safe and accessible, as well as ensuring accurate reporting to allow for effective management and decision-making. It is important to weigh each objective in each situation of the process and product lifecycles since the objectives are opposed. In this regard this section will discuss the following cases that fit onto this hierarchical level:

1. Design of manufacturing systems
2. Work management with AI
3. Planning and scheduling the production of IPPS
4. Industrial reports based on Natural Language Processing

4.1 Design of manufacturing systems

Manufacturing of products requires the combined and coordinated effort of human resources, equipment, and machinery. The design of manufacturing systems can become highly complicated due to the multitude of possible solutions and the geometrically increasing engineering time needed to find an optimal solution. As the number of variables and constraints, which depend on the types of products, resources, and processes, in the system design problem increases, traditional optimization algorithms struggle to find the optimal solution in a reasonable amount of time. This issue stems from the fact that the design of manufacturing systems falls under the classification of NP-hard problems, for which no efficient algorithm currently exists to find the optimal solution. Therefore, the design of manufacturing systems requires innovative approaches and techniques to overcome these challenges and find the best possible solution.

AI can play a crucial role in the case of manufacturing systems design as it can effectively handle the complexity and scale of these problems. By utilizing advanced algorithms such as machine learning and deep learning, AI can analyze large amounts of data, uncover patterns, and provide insights that inform the design process. The implementation of AI in the manufacturing systems design enables automated search processes, allowing human resources to undertake other tasks. Furthermore, AI can serve to identify trade-offs between different design decisions and provide insights into the impact of changes to the manufacturing system. In practice, AI can be employed for predictive modeling and optimization using machine learning algorithms, and design and simulation through AI-powered simulations. Thus, the integration of AI into the design of manufacturing seems to have the potential to significantly improve the efficiency and effectiveness of the design process while improving the outcome and yielding more efficient production processes.

In this perspective, several methods of deriving assembly line design alternatives and evaluating them against multiple user-defined criteria have been presented (Michalos et al., 2012). Process requirements such as the process plan, and alternative possible solutions, such as the joining technology to be used can be provided as input to the AI system (Figure 41). The system based on the input generates and searches a large number of technically feasible designs. Then the alternative design is evaluated under a number of multiple criteria e.g., investment cost, availability, equipment reuse, production volume, and flexibility. As a result, suitable alternative cell designs are generated and proposed to the designer (Figure 42). The discussed method can translate a cell design decision-making problem into a search one, and it can, therefore, be attacked in a more systematic way using AI. The method was implemented in the form of a decision support tool, capable of identifying good quality solutions. An intelligent search algorithm was employed to solve the design problem at hand.

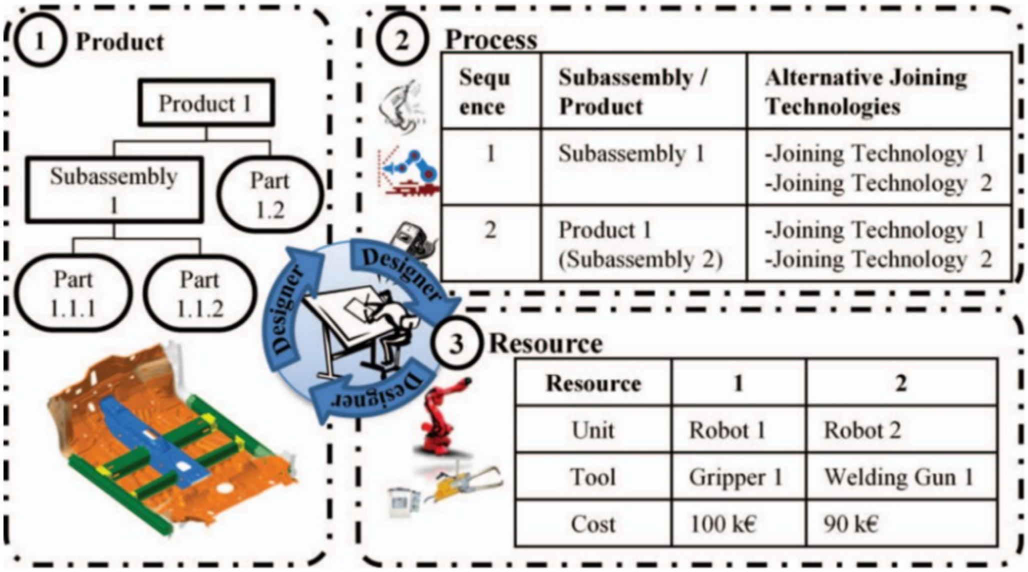

Figure 41. Alternative designs for product design, (Michalos et al., 2012)

(a) Spot welding configuration with 2 robots and fixtures

(b) Spot welding configuration with 3 robots and fixtures

(c) Spot welding configuration using cooperating robots

Figure 42. Alternative cell designs created through a generative design process, (Michalos et al., 2012)

4.2 Work management with AI

The manufacturing work environment is increasingly becoming digital. In the digitalized factories, there is a need for new kind of collaboration between production systems and factory workers. Capacity planning of human and material resources can be done holistically to maximize productivity and well-being at work simultaneously. Different work tasks can be measured, physical and cognitive workload can be followed and worker information can be considered. Combining the information of the work environment and worker preferences and skills can greatly enhance the wellbeing and satisfaction of the workers and empowering work communities.

The AI Foreman concept solution that carries out work management with AI has been proposed as a counter measure. The pilot is part of the Reboot IoT Factory initiative where one of the main goals was to study how new technologies can be used to improve the well-being and productivity of human workers[11]. AI Foreman tracks production and records skills data to a matrix that collects the expertise of each worker. The tasks are allocated based on a worker's digital twin, which includes personal preferences and skills. Each employee can then access their own personal data through the MES system. Also, feedback of

[11] Reboot IoT Factory, https://rebootiotfactory.fi/labor-at-digital-work-environment/)

various work phases can be collected and used so that the employee's day consists of pleasant and sensible tasks. The system monitors the daily progress, resourcing and how the goals are met. It helps to ensure that the team has as little obstacles as possible disturbing their work. In a longer term, the information can also be used for adopting new skills and career development.

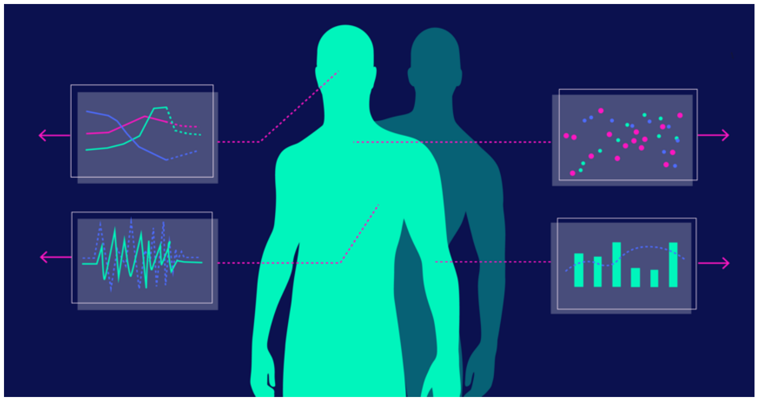

Figure 43. AI Foreman concept[12]

When optimising work practices, it is essential to consider ethical and legal aspects and engage workers. Making decisions and gathering data about human resources requires empathy, control, involvement as well as agile, appropriate, and data-intensive tools. AI Foreman has shown promising results and the feedback from the employees is very positive. This paves the way towards AI-powered work communities and collaborative human-AI systems, where human operators can pre-process data, critically interpret the AI results and train AI solutions similarly as new colleagues.

4.3 Planning and scheduling the production of IPPS

In product-oriented Industrial Product Service Systems (IPSSs) the customers benefit from the combination of a product that offers some functionalities and a set of services. IPSS supports the provision of services which can be offered by the product manufacturer. The services can offer a wide range of functionalities that can range from ensuring the product's original functionality to augmenting the original functionality of the product. The shifting of a company to IPSS poses many challenges such as the changing of the company's business model. One of the most important challenges for the establishment of IPSS is the appropriate planning of the resources for production, deployment, and installation into the customers' site. In (Alexopoulos et al., 2017) a multi-criteria resource planning method and tool for optimizing the production, delivery, and installation of IPSS has been developed. The solution employs an AI technique for generating alternative IPSS production and installation plans and evaluating them on performance measures for production and installation such as time and cost. Moreover, through the integration of the planning tool with the IPSS design phase, information for generating the Bill of Process and Materials is presented. The objective of the AI planning method is to find an optimal solution that decides what IPPS equipment (e.g., sensors) suppliers to select, which resources (e.g. IPSS service installation technicians), and when they should perform which processes/tasks at IPSS provider or customer site. The planning method proposed in this work is based on the approach proposed by

[12] https://rebootiotfactory.fi/rebootiotfactory/future-work-with-ai-foreman-in-digital-factory/

Chryssolouris and Lee (1994) and it defines the approach for assigning a set of resources to a set of tasks under multiple and often conflicting optimization criteria.

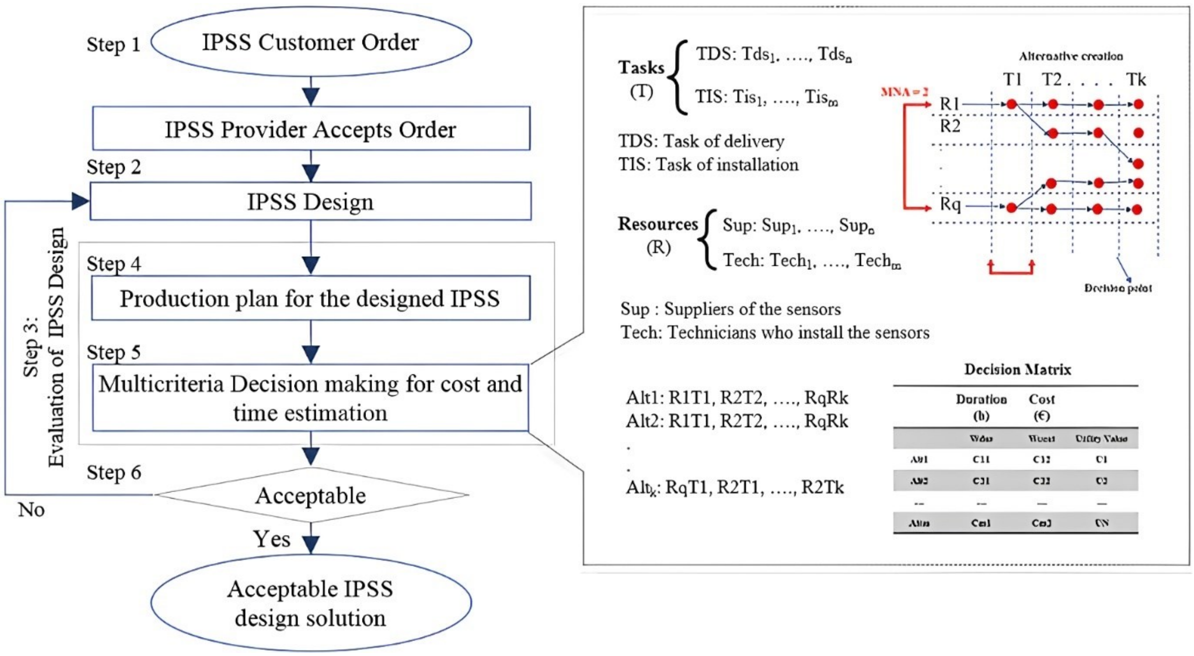

Figure 44. Industrial Product Service System production and installation planning flowchart (left); intelligence search for evaluating different option (right), (Alexopoulos et al., 2018)

4.4 Industrial reports based on Natural Language Processing

Production, maintenance or inspection processes require semi-structured reports containing metadata, text and images. They serve as a support for the transmission or capitalisation of information. Due to the lack of available time and the working environment, the reports are poorly written and/or incomplete, making them difficult to exploit through automatic processing. In addition, reports are written "on the way back to the office", which often results in a loss of information. NLP tools could be used to simplify the report writing process by automatically structuring dictated reports for integration into automated processes.

Written reports are one of the main ways that organizations capture and pass on knowledge. But to be effective, an organization's knowledge management system needs complete, clearly-written reports. For instance, DIVORA is a smart voice-dictation tool, developed in the scope of Factory Lab, that can automate the generation of written reports. The idea is for users to be able to dictate their reports into a mobile device right from the worksite. DIVORA prototype aims to simplify the process of writing structured reports in the industrial context by adapting automatic written language processing tools for the analysis and interpretation of voice dictation.

In the DIVORA[13] prototype, a first module leverages a speech recognition technology to convert speech into text. The text then goes through a second module, built on CEA-List's LIMA[14] multilingual analyzer, where significant terms of the report and the semantic relationships between these terms are identified. One problem with this type of tool is the difficulty of adapting the artificial intelligence models to the domain of the use cases treated: specific vocabularies, syntaxes, languages and knowledge. To do this, the CLIMA tool (LIMA Configurator) facilitates the configuration.

The development of demonstrators focused on two use cases: the generation of an inspection report for a forklift truck and the generation of a report for site monitoring. The demonstrators are functional and produce clear reports, possibly presented in the form of tables. In addition to saving time, they guarantee optimal information quality. DIVORA will soon be adapted to other professions, notably in the fields of health and e-commerce.

Work is being carried out to integrate data-mining tools into Electronic Document Management (EDM) technologies. AI technologies will ease extraction of technical terminology, document matching, document categorization, structuring of business concepts. AI will also drastically improve semantic search engines, synthetic view of documents and adaptation to the domain for greater user autonomy.

The technological stakes are multiple and ambitious: making LIMA/CLIMA evolve for the needs of EDM, capitalization of evolutions of the search engine according to the cases of use treated (Search by keywords, entities, relations…) and cross-document exploration, development and the automatic terminology structuring theme.

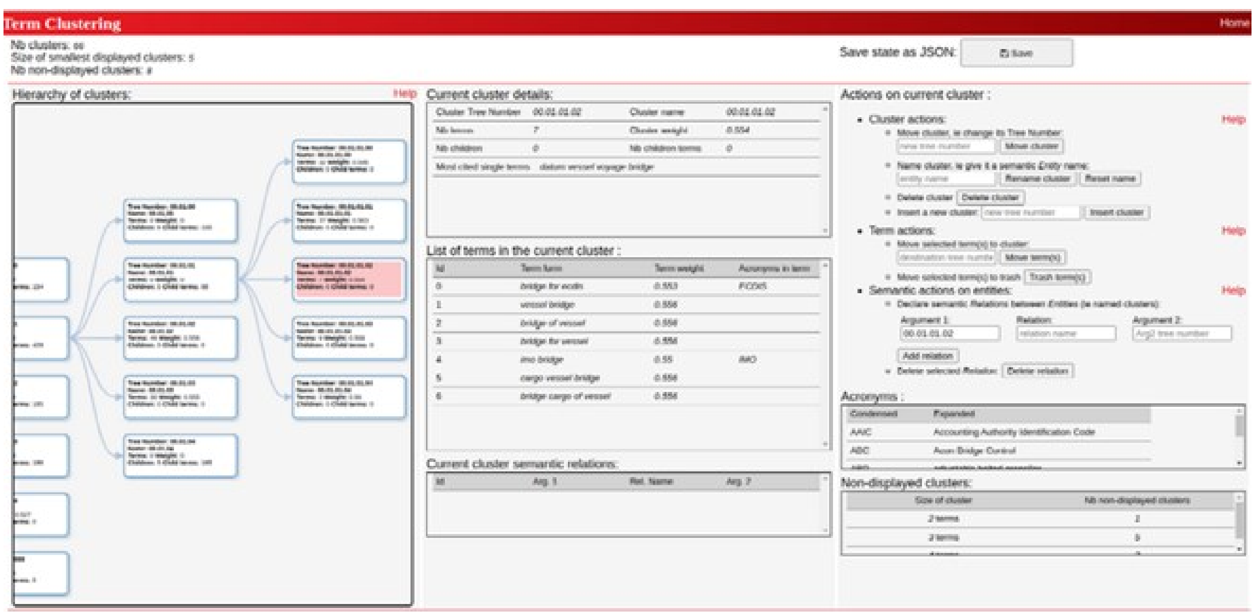

Figure 45. Semi-automated term clustering for terminology structuring by identifying key concepts of the domain (grouping of instances)

13 cea ialv, DIVORA BV, (Nov. 04, 2020). Accessed: Sep. 01, 2021. [Online Video]. Available: https://www.youtube.com/watch?v=FrwnB6XDzpU

14 “Home · aymara/lima Wiki,” GitHub. https://github.com/aymara/lima (accessed Sep. 01, 2021).

4.5 Consolidation of AI application at the System level

The AI-based enhancement of the manufacturing system's level can support multiple processes from the system's design to the digital infrastructures and ICT technologies that are required for its seamless operation. The impact that can be brought by AI solutions is possible to be reflected in KPI values. The majority of existing solutions evaluate their performance based on KPIs such as the design time required to produce AI models/Digital twins.

Regarding the design time required to produce AI models/Digital Twins, data scientists typically spent 60 to 80% of their time in 'data collection'. The knowledge graph approach (TRL 3-4) we put forward should allow to significantly reduce the time needed to collect that data. Nuance: there is a setup cost, so currently the benefit is for companies that systematically want to invest in AI for manufacturing, and less for 'one-off' implementations.

A lot of attempts to create AI models in the manufacturing domain fail due to the fact 'black-box approaches' are used to infer cause-effect relations on the one hand and train models on the other hand. Especially in a high-mix-low-volume context with limited data and many process and configuration parameters, these approaches do not yield successful AI algorithms. By capturing explicit and implicit knowledge in the knowledge graph, a much higher success rate can be achieved.

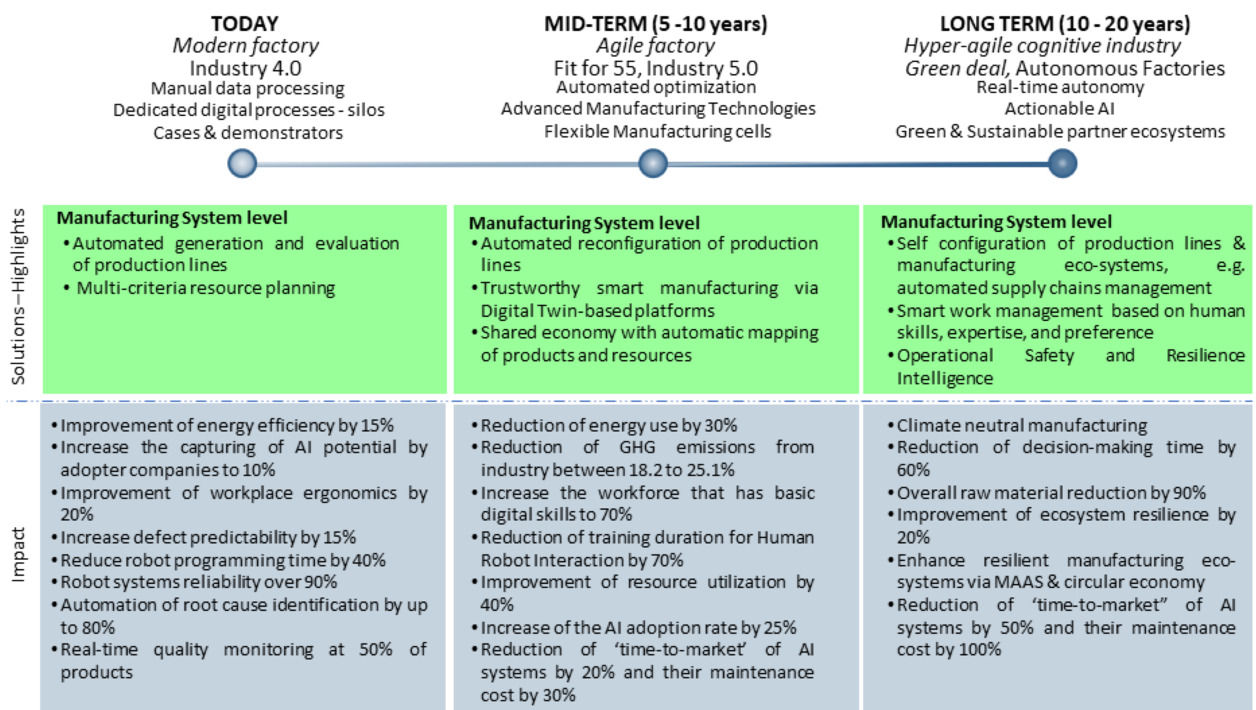

Figure 46. Current status and Future Vision for the adoption of AI at the Manufacturing System level

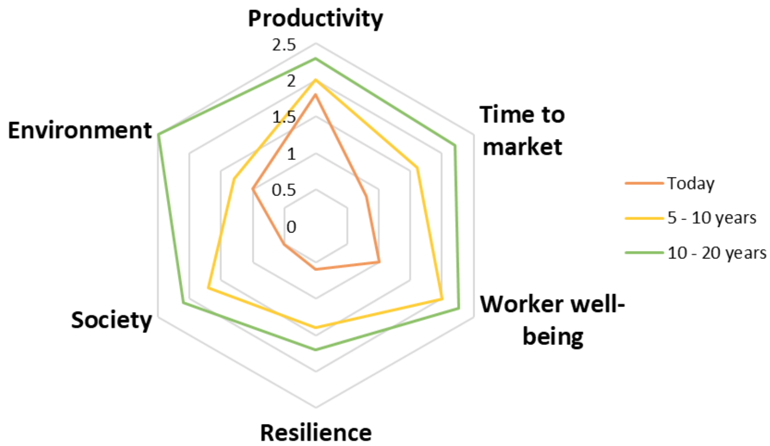

Figure 47. Degree of vision achievement

If the data that is going to fit the AI model is not representative enough of the problem to be addressed, the probability of success drastically decreases for obvious reasons. The proper digitization of the system or systems under study is crucial in order to be able to compute and measure the KPIs over time and optimize them by means of an AI-based, data-driven approach. This is done by having a clear idea about what to measure and how from the system under study, at the conceptualization and design stage of the AI solution. The expert knowledge and a deeper problem understanding from a business perspective must support this process.

5 Cross-cutting aspects of AI in Manufacturing

This chapter deals with aspects that are relevant to all the levels of the defined manufacturing hierarchy and the identified technologies. Issues such as knowledge representation, synthetic data generation, and platforms for AI applications in manufacturing are discussed.

5.1 Knowledge representation: Modelling & Semantics as enablers of smart decision-making

AI in manufacturing covers a very diverse range of applications from defect detection to more complicated applications such as plant predictive maintenance, as presented in the previous sections. AI is especially beneficial in supporting **tactical** (fi. 'where should I install an additional QI system') and **operational** decision making (fi 'optimally combining parts to ensure the end-of-line quality') *at the level of the design and (re-configuration) complete factory lines,* or even reaching beyond the manufacturing silo towards *the product design* ('Based on my end-of-line test, do I really need such a tight geometrical tolerance on this shaft in order to have the desired performance'). A crucial step in the "AI lifecycle" of all these applications, is the analysis of (raw) data recorded by sensors and software, often carried out by data scientists, in order to generate actionable insights. Typically, this is **a complex and cumbersome process.** The reasons for this are manifold:

- Data is often *physically spread across multiple silos within the organization*. This makes it hard for a data scientist to keep a correct overview of all data, and how it is connected.
- The data sources (inputs from human operators and designers, Manufacturing Operations Management software, machine sensors) and types are very *heterogeneous*: data may be *relational* (product X was tested by operator XYZ and assembled in workstation ABC), *blob data* (e.g., images

from quality inspection systems), *timeseries data* (fi. Cooling liquid temperatures), graph data, etc. and therefore, also typically stored in different storage mechanisms.

- *Technical level data does rarely correspond to domain level data*: a concept in a problem domain often maps to multiple technical data concepts (e.g., tables), data may not be organized or named in an intuitive way, data formats may not correspond their semantics, etc. In one of our industrial cases, retrieving all orders for a customer involved joining more than 10 tables.
- Important c*ontext information about the data is often implicit:* data may be recorded under different conditions, by different operators etc. and this meta-data is often not captured.
- Existing production knowledge (fi. process FMEAs, Ishikawa diagrams, operator experience) are most often still *tacit knowledge* and not easily reusable.
- Previously obtained insights typically take the form of ad-hoc analysis scripts (in e.g., Databricks) and reports. This makes it hard to reuse those previous insights and knowledge when starting a new data analysis experiment.

Knowledge graph approaches have been proposed to make the data analysis processes for AI applications more efficient. The knowledge graph is used as the harbor of all data, information and knowledge related to a manufacturing system. It is structured according to the conceptual model of a knowledge domain, i.e., product design and its manufacturing process. Therefore, domain experts can use real-world concepts, vocabulary and relationships between these concepts to describe and solve problems related to the domain (e.g., what-if analysis, training AI models, etc.). During the AI lifecycle, the manufacturing knowledge graph is the gateway to find and store all knowledge about a manufacturing process that exists within an organization. It specifies what historical data exists, how it is related, from which sensors this data was collected, to which manufacturing process it was related, who was involved, what correlations may exist, what physics models are involved, which data experiments have been conducted in the past, what machines, sensors, products, operations exists and how they are used in the manufacturing process, etc. All this data, information and knowledge together form the "historical digital twin" of the manufacturing system. The term "historical" digital twin is used since this digital twin contains the historical information of the manufacturing system, as opposed to the more traditional "streaming" digital twin that mirrors the live state based on streaming data of a manufacturing system. The approach is illustrated in Figure 48 .

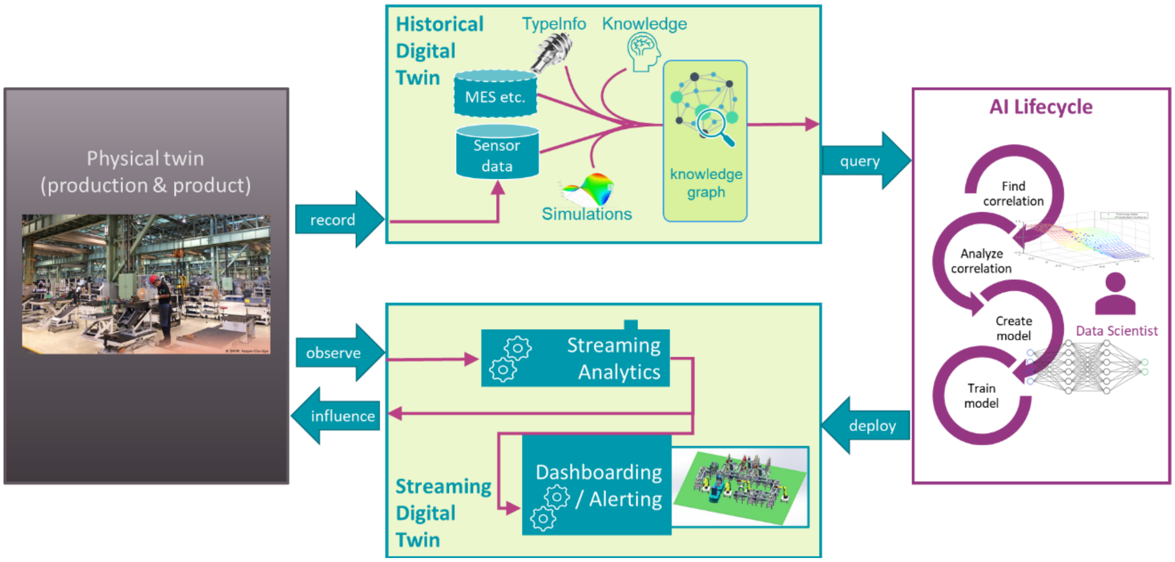

Figure 48. Knowledge Graphs for AI in manufacturing, (Meyers et al., 2022)

In order to being able to support the data analytics step in the AI lifecycle, the manufacturing knowledge graph has to exhibit a number of characteristics:

- **More than data**: it models data, but also information and knowledge about this data, where all concepts are defined in terms of the problem domain, making them intuitive to domain experts. For instance, to avoid that, data scientists have to perform an enormous amount of black box correlation analysis, known or suspected influence relationships can be captured in the knowledge graph.
- **Typed graph**: the knowledge graph can be seen as linked concepts, so it has a graph structure by nature. Concepts are explicitly typed in order to define and impose structure.
- **Explorable**: given the potentially large span of content of the knowledge graph, it must be possible to explore its structure, to learn what concepts exists and how they are related.
- **Queryable**: during the AI lifecycle, data scientists must be able to query specific data, information and knowledge, without needing to know its technicalities, e.g., where data are stored, with what tool, etc. Users may query for data, but also for information and knowledge, e.g., have we done a data science experiment that investigates the correlation between two given physical entities?
- **Virtual data**: Given the large amount of data in an organization, and the highly optimized storage of this data, the knowledge graph needs to support data virtualization. Existing technologies like Spark data frames (in e.g., Databricks) provide such support and are thus, interesting for data scientists. Alternatively, querying the knowledge graph may result in technical-level queries. In any case, the user is shielded from having to compose the technical database queries, having to learn their format, location, schema, etc. Furthermore, on-demand (on-the-fly) calculations of data, by e.g., using an algorithm or simulation model can be stored explicitly in the knowledge graph and be executed on demand.
- **Evolving**: as the manufacturing system produces new data and structurally changes over time, by definition, the knowledge graph evolves with it, as also implied by the term 'historical digital twin'. This means that a query to the knowledge graph, is in fact a query to that particular snapshot in time of the knowledge graph. The same query may yield a different result at a different point in

time. The evolution of the knowledge graph needs to be made explicit in order to make e.g., data experiments reproducible, and reusable.

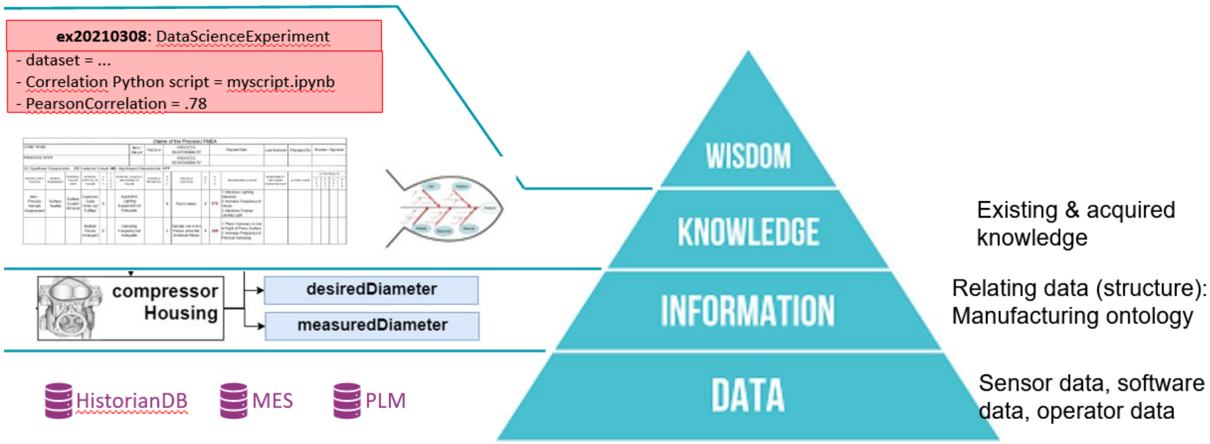

Figure 49. Data, Information, Knowledge, Wisdom (DIKW) pyramid

The implementation of the concept of manufacturing knowledge graphs has been performed using two major technology stacks, i.e., metamodeling and semantic web technology. A metamodel-based knowledge graph focuses more on strong typing and constraining all concepts in the domain. It provides a more natural integration in a software engineering process. A semantic web based knowledge graph, sometimes called ontological knowledge graph, focuses on common vocabulary, categorization and relationships of concepts for large domains. In contrast to metamodeling, it allows automated reasoning based on an open-world assumption, which often maps better to reality. Ontology engineering has been used in several disciplines to gain a better common understanding about a domain. In software engineering-related projects, RDF and OWL are de facto standards, popularized by the Semantic Web, which intends to make the Internet machine-readable by structuring its metadata. Well known success stories in other domains are DBpedia, a formalization attempt for Wikipedia that allows querying its resources and links to related resources, and the Google Knowledge Graph, which is able to extract specific information on search results in an infobox. In different areas, ontologies emerged that standardize the complete domain. Especially in life sciences this proved to be very successful (e.g., the Gene Ontology in bioinformatics, Plant Ontology in biology, etc.). In manufacturing, similar initiatives exist, like the Ontology for Sensors, Observations, Samples, and Actuators (SOSA). Yet, in contrast to the successful examples from other domains, knowledge graphs in manufacturing are still very rare, mainly due to the very heterogeneous data and knowledge that has to be dealt with. For instance, how to formally encode existing knowledge from process FMEA and or Ishikawa diagrams in a knowledge graph is still largely unexplored.

The choice of core technology also has an effect on the peripheral technologies of the knowledge graph (and hence on its characteristics such as the queryable/explorable aspects mentioned above). For example, SPARQL is an out-of-the-box query language for ontologies, and we have been using GraphQL for querying metamodel-based knowledge graphs.

The main advantage of using knowledge graphs in the data analysis phase of the AI lifecycle for manufacturing systems is that they make data, information and knowledge available in a unified way, at the knowledge domain level rather than the technical implementation level, thereby breaking the traditional data silos. Currently, knowledge graphs in AI for manufacturing are not yet common ground.

This especially limits the application of AI on the system level, as it is very hard to find the relevant scattered data and knowledge when conducting data analysis. In manufacturing companies, the amount of collected data is huge, as well as the amount of implicit knowledge about the data and the manufacturing processes that hide behind them. Especially in the manufacturing industry there is a lot of unleveraged domain knowledge, more than in other (purely data-driven) application domains. If an organization is able to capture and unify such extensive knowledge using a knowledge graph, we believe that this will be a key enabler to leverage their AI potential and reduce the time necessary for carrying out data analytics activities on the one hand and increase the success ratio of building AI systems for the manufacturing industry.

5.2 Platforms & infrastructure for AI-based decision-making in manufacturing

Heterogeneous and distributed data structures, variety of digital implementation frameworks, hybrid edge-cloud architectures, lack of standards for the semantic description and interoperability between heterogenous systems and devices, latency requirements as well as lack of standardized AI solution components management imply making huge effort to manage share datasets and AI models between stakeholders and industrial assets avoiding efficient and agile production (Lukas Rauh et al 2022). There are various principles to reduce effort and push industrial AI by focusing on the comprehensive lifecycle (S. Amershi et al. 2019, L. Baier et al, 2019, R. S. Peres et al 2020):

- **Data Governance** including Policies to ensure that data is accurate, consistent, complete, secure, private, accurate, available, and usable. About 80% of the time consumed in most AI and ML projects is related to data management, preparation, and engineering (Cognilytica, Ed “Data Preparation & Labeling for AI 2020,” 2020).
- **High Degree of Automation** including high quality process.
- **Flexible manufacturing** process to allow workloads and strategies to customized production in the face of external changes.
- **Standardization Interoperability – Plug and Produce**: Standardization and interoperability are key for the successful implementation of this digitalization strategy (Iñigo, M. A. et al. 2020). Standardized Digital twin per each industrial device for multiple conversations and operations for compatible manufacturing environment.
- **AI Semantics** would ensure transfer immediately in a federated ecosystem the use of data and algorithms for a specific context.
- **Federated Environment.** Multiple Nodes using data from similar devices would improve AI models and productivity**.**
- **Standards:** Data structure from definition of devices using AAS, communication through OPC-UA, MQTT and Structure Business Layer with AAS submodels including AI semantics would facilitate operations along value chain.

Today, it is mandatory to access a trusted infrastructure to ensure the continuum of data from the field to the cloud to host and manage data. This continuum is a vital infrastructure whose security and sovereignty must be ensured so that companies can trust and take full advantage of digitization. The lack of secure and sovereign solutions for the cloud on the edge (also called far edge) remains the missing link slowing down the digitization and slowing down manufacturing industry. The "far edge" requires business knowledge and the need to take into account interfaces with the legacy environment over long periods of time. The opportunity is exciting as hyperclouders are slow to address it. Aligned with this need the french project called OTPaaS [15](Platform as a service for OT) targets the massive digitization of companies by offering a cloud suitable for the digitization of the field that is compatible with Gaia-X and easy to use by companies including SMEs. The OTPaaS project relies on technology providers to build sovereign solutions for the distribution of data and processing capacities between IoT, IT and the cloud and aims to expand in a second step to European suppliers to offer a strong infrastructure with large services.

Several architectures have been proposed for the combination of shopfloor data with edge and cloud computing services. For instance, Figure 50 shows a suggested architecture towards exploiting edge, and cloud capabilities for processing data from the shopfloor with AI-based approaches. A number of relevant features includes the coupling of AI to digital twins, data modeling, incorporated engineering knowledge, interactive visualization, ontologies/semantics and different data sources (PLM, Sensors). Moreover, adjustable data granularity, and flexible/Purpose oriented data collection is enabled, whereas cloud and IIoT services can be used based on authorization to ensure security to people or algorithms. In this way it is possible to overcome barriers due to lack of access to data, lack of data, limited data, split to atomic process steps, or unbalanced data.

On a manufacturing shop floor, context-aware intelligent service systems can be used to provide AI services to people on the shop floor and back office. Industrial Internet of things (IIoT) context-aware information systems (Alexopoulos et al., 2018) can be employed to support decision support for mobile or static operators and supervisors. Such systems may combine key IIoT concepts such as multi-layered, service-oriented architecture, which integrates several subsystems, such as sensor data acquisition with concepts for developing AI systems that utilized contextual information collected. As discussed in (Alexopoulos et al., 2020), such architectures can be combined with the digital twin concept into building frameworks for deploying AI applications in manufacturing settings (Figure 50).

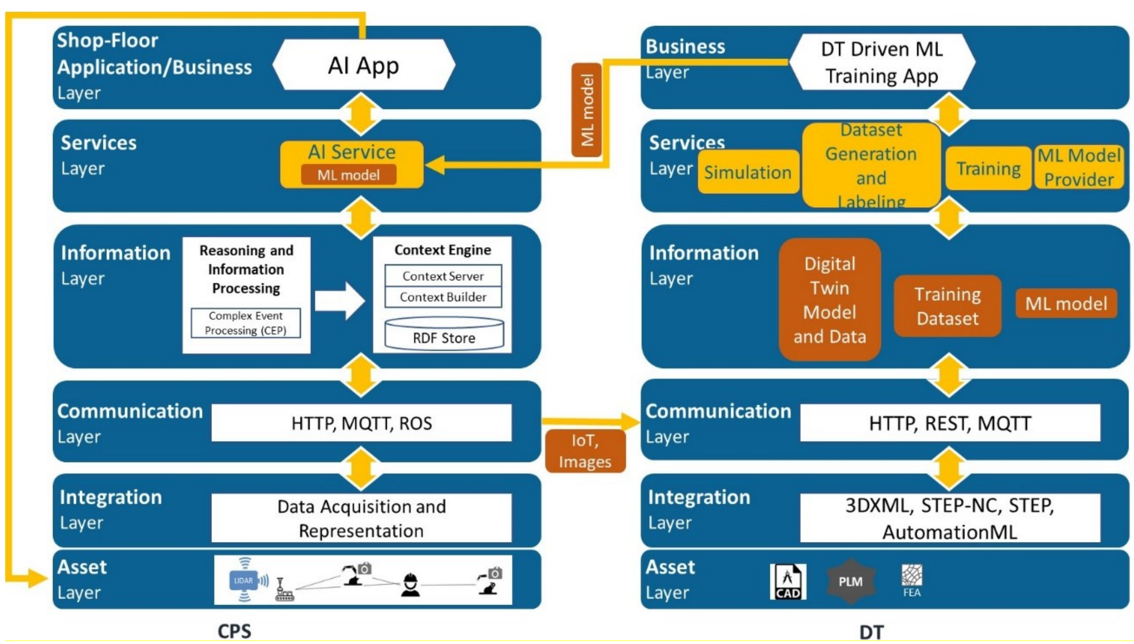

Figure 50. Digital twin for the development of machine learning-based applications for smart manufacturing, (Alexopoulos et al., 2020)

[15] https://www.linkedin.com/company/otpaas/?viewAsMember=true%20)

5.3 Data spaces for AI development and deployment

Data and data sharing are key ingredients for the implementation of AI. However, to solve the challenge of fueling AI models with enough quantities of quality data a collaboration between organizations is needed that enables a) data sharing for AI, and b) execution of AI algorithms. Organizations in order to share their data, they should have been guaranteed some level of trust and some level to which they stay in control over who can access their data and for what use, i.e. data sovereignty[16]. Recently, the concept of data spaces has emerged for the implementation of industrial data spaces under data sovereignty principles and the most notable initiatives are the Gaia-X[17] and International Data Spaces Association (IDSA)[18].

Gaia-X "*is an initiative that develops a software framework of control and governance and implements a common set of policies and rules that can be applied to any existing cloud/ edge technology*. They have several lighthouse pilots aiming to demonstrate Gaia-X capabilities in manufacturing such as Catena-X[19] focusing on the automotive value chain and EuProGigant[20] which is cross-sectorial and cross-the-border in the manufacturing value chain. Similarly, IDSA envisions "*to create a future where trusted partners, of all sizes and from all industries, can securely share data while maintaining self-determination and control.*" The Smart Connected Supplier Network (SCSN)[21], driven by TNO and BrainportIndustries in The Netherlands, is a data standard that makes the exchange of information in the supply chain more efficient, so that companies can share data more easily, reliably and quickly over trusted dataspaces such as IDSA and Gaia-X. Another stream of stakeholders that have a key role in supporting industry into the adoption of advanced AI technologies such as the integration to common data spaces are the Digital Innovation Hubs (DIH) as well as the Testing and Experimentation Facilities (TEF) for manufacturing[22]. TEFs are expected to contribute with sharing of data (e.g., robotics operations or production equipment data from OPC-UA servers) for enabling the development of smart manufacturing AI services. In a similar manner, under the Digital Europe Program (DEP) the DataSpace4.0[23] Coordination and Support Action (CSA) is creating a pathway and governance model for scale-up of cross-sectorial data spaces for manufacturing.

On a smaller scale research and innovation activities have been launched in the context of EU research and innovation framework. These projects validate data sharing technologies in targeted value chains and help to remove the technical obstacles when setting and deploying manufacturing dataspace. MARKET4.0[24] H2020 has employed IDSA technology to develop a marketplace for manufacturing equipment and services based on trusted data and services. MUSKETEER H2020[25] is using IDSA technology for setting-up federated AI for manufacturing companies. AMABLE H2020[26] provides digital services to enable uptake of Additive Manufacturing for SMEs on top of IDSA powered data ecosystem. FLEX4RES[27]

[16] NL AI Coalition, 2022, Towards a Federation of AI Data Spaces
[17] *Gaia-X 2022, www.gaia-x.eu*
[18] *IDSA 2022, https://internationaldataspaces.org/*
[19] *Catena-X, 2022, https://catena-x.net/en/*
[20] *EuProGigant 2022, https://euprogigant.com/en/*
[21] *SCSN 2022, https://www.brainportindustries.com/en/factoryofthefuture/smart-connected-supplier-network*
[22] AI-Matters, https://ai-matters.eu/, accessed online April 2023
[23] DataSpace4.0, https://manufacturingdataspace-csa.eu/, accessed online April 2023
[24] *MARKET4.0 H2020, www.market40.eu*
[25] *MUSKETEER H2020, https://musketeer.eu/*
[26] *AMABLE H2020, https://www.amable.eu/*
[27] FLEX4RES HE, https://www.flex4res.eu/, accessed online April 2023

utilizes data spaces for developing AI services to support resiliency in manufacturing data spaces (Alexopoulos et al., 2023). However, although these projects have produced some preliminary positive outcomes, they are still fragmented in terms of semantic interoperability (i.e., different standard or format are used for similar purposes), technical interoperability (e.g., different data connectors are used in different projects that are not necessarily compatible) as well in terms of data governance structures and data policies.

Figure 51 presents a conceptual approach for building and deploying AI applications over data spaces technology utilizing the IDSA Reference Architecture. Data are shared between the data providers/owners (e.g., OEMs) and data consumers (e.g., data analytics developer) for developing data-driven (e.g., Deep Learning) AI applications. Then through a secured App Store these AI applications can be used by the users.

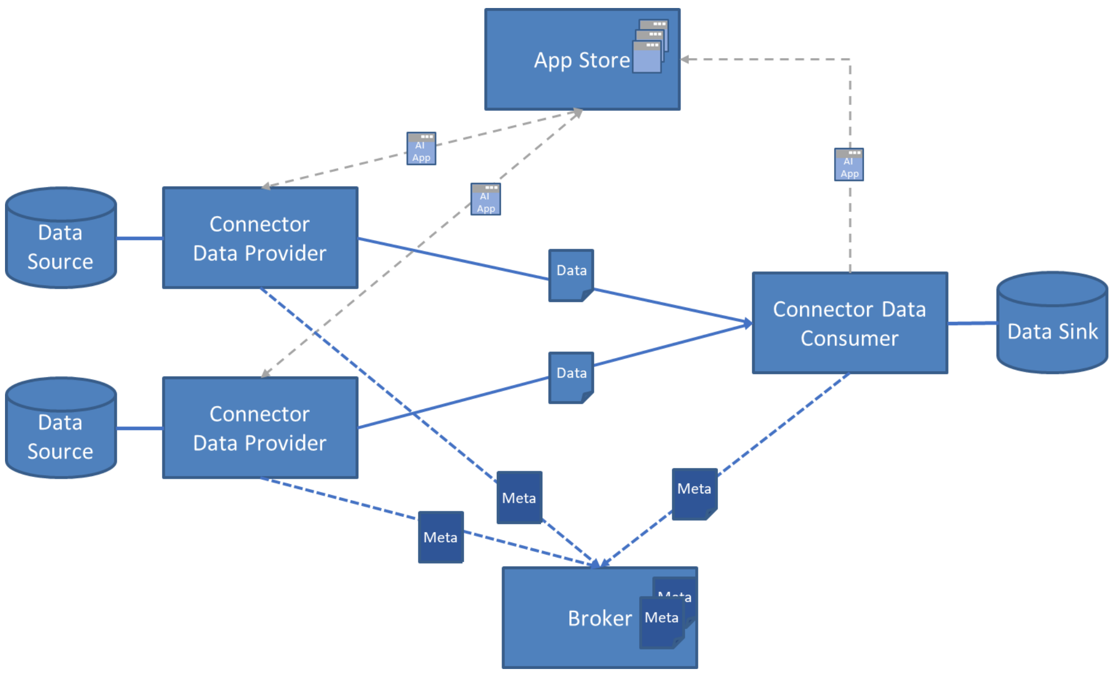

Figure 51: AI in data spaces (adapted schema based on IDS RA[28])

5.4 Digital Twin for Synthetic Data Generation

AI applications based on Machine Learning (ML) methods are widely accepted as promising technologies in manufacturing. However, ML techniques require large volumes of quality training datasets and in the case of supervised ML, manual input is usually required for labeling those datasets. Such an approach is expensive, prone to errors and labor as well as time intensive, especially in a highly complex and dynamic environment as those of a production system. Digital Twin models can be utilized for accelerating the training phase in ML by creating suitable training datasets as well as by automatic labeling via the simulation tools chain and thus alleviating the user's involvement during the training phase. Frameworks for generating synthetic datasets (e.g., synthetic images) through the use of simulation tools and the DT concept to serve the development of ML models have been presented (Alexopoulos et al., 2020). The

[28] IDSA 2019, Reference Architecture Model 3.0

architecture in Figure 52 represents the main entities of such a framework which are the following: a) the CPS that links the physical world, such as a machine or robot on the factory floor, to the cyber through the creation of a digital thread between them, thus formulating Cyber-Physical-Production System and b) the DT that represents the virtual model of the physical system or process, it is linked with CPS entity through the data communication channel and it is capable of replicating aspects of the behavior of the CPS system. Both CPS and DT stacks are defined and implemented based upon the same layered architecture approach. However, the layers are different for each stack, DT and CPS, as they are implemented and can be deployed independently.

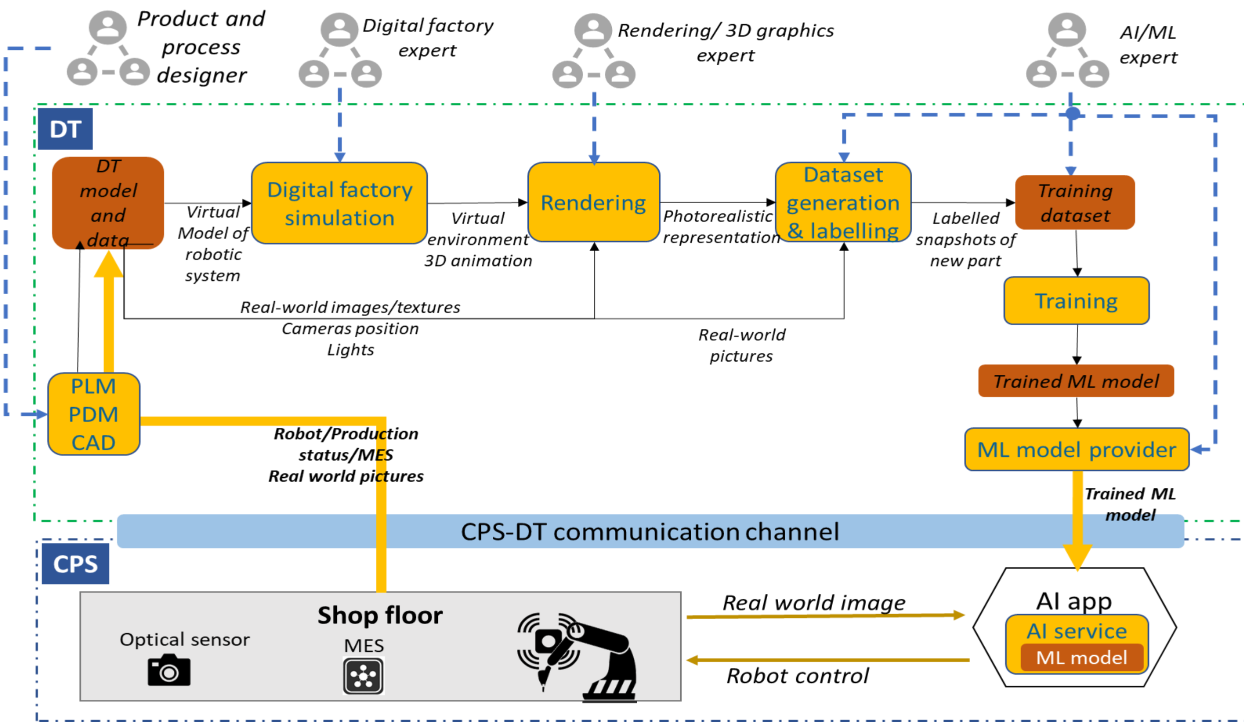

Figure 52. DT-driven ML for self-adaptable handling of product variations by an industrial robot, (Alexopoulos et al., 2020)

5.5 Education and training aspects

The accelerated technological evolution creates a dynamic environment regarding the required future skills and competencies. In particular, the development of AI technologies is expected to stimulate important changes in jobs, as well as the necessary skills that employees must incorporate. Diverse challenges regarding gaps and shortages of workforce skills and competencies, can be identified in different industrial sectors, which in turn have stimulated the funding of several projects to cover the knowledge and competences gap by using novel knowledge delivery mechanisms, and modern ICTs. A number of relevant research projects have treated the improvement of educational schema with respect to Industry 4.0[29], or they have focused on delivering effective training courses to enable the uptake of

[29] https://www.eitmanufacturing.eu/news-media/activities/smart-educational-framework-for-digitalization-smartdigi/

industrial Internet of Things (IIoT) technologies and smart manufacturing systems[30] e.g. tutorials on cyber physical production systems [31].

The EU community needs to structure services to train the next generations of young people so that they can easily cope with the new models of more automated and connected industry, with the skills and abilities that the work market demands in light of AI-based technologies. Likewise, it is also necessary that the new generations incorporate a critical spirit regarding the design, implementation and development of these technologies, as well as uniting education in values that prioritize reflexivity, inclusiveness, diversity, equity, sustainability or responsibility. That is why coordinated approaches are needed between administration, industry, academia, and civil society, to facilitate these transformations that enable the training of active workers who will face this transition, as well as the new generations that will lead these processes of change. Tools that could enhance training efficiency include Mixed Reality tools, which provide online support to workers on various tasks being executed and offline training for various manufacturing processes.

In addition, the education services should be grounded on successfully implemented education paradigms in manufacturing, such as the Teaching Factory concept. The Teaching Factory concept has introduced as a two-way knowledge communication between academia and industry (Mavrikios, Georgoulias, and Chryssolouris 2018). The Teaching Factory paradigm provides a real-life environment for students and research engineers to develop their skills and comprehend the challenges involved in everyday industrial practice (Chryssolouris, Mavrikios, and Rentzos 2016) and has been applied in a case study about the collaborative design of machine tools (Stavropoulos, Bikas, and Mourtzis 2018), real-life industrial pilots involving construction equipment factories (Rentzos et al. 2014) as well as industrial automation companies (Rentzos, Mavrikios, and Chryssolouris 2015). In more detail, the Teaching Factory paradigm aims to align manufacturing teaching and training to the needs of modern industrial practice. This is achieved by educating future engineers and upskilling/reskilling professionals and workers with new curricula to cope with the increasing industrial requirements of the factories of the future, whereas the innovative ICT configuration is employed to facilitate the interaction between industry and academia.

It is expected that a centrally coordinated pan-European network of teaching factories providing training and upskilling services will accelerate the enabling the workforce transition towards smart. This Network will provide an orchestrated effort in providing access to a common training framework (methodology, content, and material) linked with professional education and certification based on in-situ training and access to latest advanced manufacturing technologies. For instance, the teaching factories network could establish links with VET and C-VET programmes. The teaching factories network should comprise physical testbeds and DIHs (coming from previous R&D results) revamped and integrating the baseline technologies and the overall digital and AI-based manufacturing concept. The physical testbeds will serve on-site training on the emerging AI-based technologies.

[30] https://www.eitmanufacturing.eu/news-media/activities/factorybricks-smart-learning-home-for-the-management-of-connected-factories/
[31] https://www.eitmanufacturing.eu/news-media/activities/the-smart-manufacturing-paradigm-a-tutorial-introduction-on-cyber-physical-production-systems/

5.6 Ethical use of AI

AI has shown great progress during the last decade, but at the same time has also raised great questions surrounding its development and implementation in various sectors (Stahl and Wright 2018). AI applications including facial recognition, predictive prognosis, biometric markers or conversational interfaces has created a long list of socio-ethical dilemmas to be addressed (Echeverría and Tabarés 2017; Floridi et al. 2021). Focusing on the industrial manufacturing sector, the socio-ethical challenges relate to the opacity that accompanies a large number of AI systems (Robbins 2020), as well as the inability to understand the decision-making logic that in turn lead to a lack of trust by the people who use them in their daily routines. That is why these AI systems are commonly seen as "black boxes", since even the designers of these systems have difficulty understanding them. Therefore, the end users of these systems manifest their ignorance about what is happening inside the data-driven models and are completely unaware of the logic that is used, or the data based on which decisions were made. That is why it can generate anxiety and mistrust on the part of users.

At the same time, the introduction of AI in industrial environments also raises fears and doubts about the surveillance and control to which workers are subjected with the excuse of collecting data of all kinds that can feed these systems. That is why the introduction of these technologies in industrial environments must be done responsibly. Possible breaches of obligations by employers can put at risk the privacy and other types of labor rights that workers have. This and similar types of arguments align with a growing number of criticisms of the biases that AI technologies have. The biases, coupled with the underlying uncertainty in AI in an increasing number of sectors and domains, have also highlighted the need for "responsible AI" (Dignum 2017). This Responsible AI is characterized by the inclusion, protection and safeguarding of various values of civil society that the development of technology can put at risk, and that can be displaced or not taken into account by the development of technology itself (Buruk, Ekmekci, and Arda 2020). Thus, values such as gender equality, social justice, personal autonomy, the right to privacy and others, are recurrently confronted by the development of these systems and the data with which they are built. We must not forget that the multitude of databases on which these systems are based reproduce the numerous inequalities on which our societies have been built.

That is why regulation and legislation is important, but it is not enough. For example, in Europe and within the legal framework provided by the General Data Protection Regulation (GDPR) there is the right to explanation[32] that requires a user to be informed when they have been the subject of a decision made by an algorithm and based on what parameters the decision has been made. Collecting this right is a first step, but it is clear that, as these systems are developed, there will be needs both at the regulatory level and in others. The GDPR is a pioneering legislation that does not exist in countries that are absolute leaders in this type of technology such as the US or China.

In addition to these social implications of technology that are closely related to principles of fairness and non-discrimination, the development of AI in industrial settings also feeds various anxieties regarding automation and mass unemployment (Bassett and Roberts 2020). A concern that is not new and that has been common throughout history due to the dynamics of technological change and its introduction in factories. New fears around this massive unemployment have been described by recent academic works that have explored the degree of automation of current professions in the hands of AI and that draw a less optimistic future in this regard, especially in professions that had not been targeted by automation

[32] https://gdpr.eu/recital-71-profiling/

(Frey and Osborne 2017). However, there is still a high degree of uncertainty about how these technologies will be deployed in various sectors and domains, and what their impacts will be on the work market. The constant and incessant acceleration of the needs of the work market are stimulated by the dynamics fostered by technological change and this causes social transformations with a high degree of instability and uncertainty[33].

For this reason, it is also important to "relativize" the role of automation around "possible mass unemployment" caused by technological change, since automation is only a tool and "there is nothing automatic in automation" [34]. In addition, recent studies seem to show that the problem of low demand for workforce in factories and industrial environments is not directly associated with industrial automation but rather with various factors including global deindustrialization, lack of investment, overproduction and limits of economic growth itself[35]. A responsible development of AI becomes even more important, since the development of these technologies will entail important changes in jobs, the necessary skills that employees must incorporate into manufacturing processes, etc.

Key enabling technologies – KETs – are knowledge and capital-intensive technologies, pervasive and with a systemic relevance for all industrial and economic sectors. They are expected to have an impact on high quality jobs creation, life quality improvement and sustainable development. KETs have the potential to transform existing modes of production, and thus change relationships along the whole value chain of product development, between manufacturers, suppliers, businesses, users, policy makers, and citizens. EUC has already acknowledged the need to research towards developing technologies for the benefit of society, thus there have been some projects addressing such issues such as TAILOR[36], SocKETs[37] however, the wide range of topics and issues that accompany the ethical use of AI require for consistent and coordinated research.

5.7 Explainability of AI for manufacturing

Some AI solutions potentially involve high number of parameters, which is not easy to process by human mind —some neural networks like GPT-3 (Brown et al., 2020) comprise more than one hundred billion of adjustable parameters—, such models are no longer considered simulatable (Lipton, 2018). Here, simulatability refers to the property that a “human should be able to take the input data together with the parameters of the model and in *reasonable* time step through every calculation”. In many applications in manufacturing, employing black-box machine learning models is not an issue as long as the accuracy or performance of these models is sufficiently good and comprehensibility of the model’s reasoning is not a requirement. The application of such models becomes critical if they are applied in strongly regulated environments like medical device manufacturing or in applications with high safety requirements like in human-robot collaboration. In such situations, there is a growing demand for so-called *white-box models* that are human comprehensible. To satisfy this demand, the research field of explainable AI (XAI) gained increasing interest in research and application. XAI aims for providing the meaning or the explanation of

[33] Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age. New York: Norton & Company.
[34] Smith, A., Fressoli, M., Frisancho, M. G., & Moreira, A. (2020). Post-automation: report from an international workshop. In Post-Automation Workshop.
[35] Benanav, A. (2020). Automation and the Future of Work. London & New York: Verso.
[36] https://tailor-network.eu/
[37] https://sockets-cocreation.eu/

the outcomes of a machine learning model in a human understandable form. According to Figure 53, there are several ways to achieve this goal (Burkart & Huber, 2021):

(1) *Explainable by nature (ante-hoc approach):* Instead of using opaque black-box models, the learning problem at hand is solved by means of a white-box model such as linear regression models or short decision trees. For many applications, white-box models provide sufficient accuracy and some researchers even state that in case of highly critical applications, one should avoid black-box models (Rudin, 2019). Especially in robotics, which often requires processing high-dimensional and highly complex sensor signals, white-box models are often not accurate enough and thus, one has to rely on grey-box or black-box models. In such cases, the ante-hoc approach is not applicable and the following two ways of XAI remain.

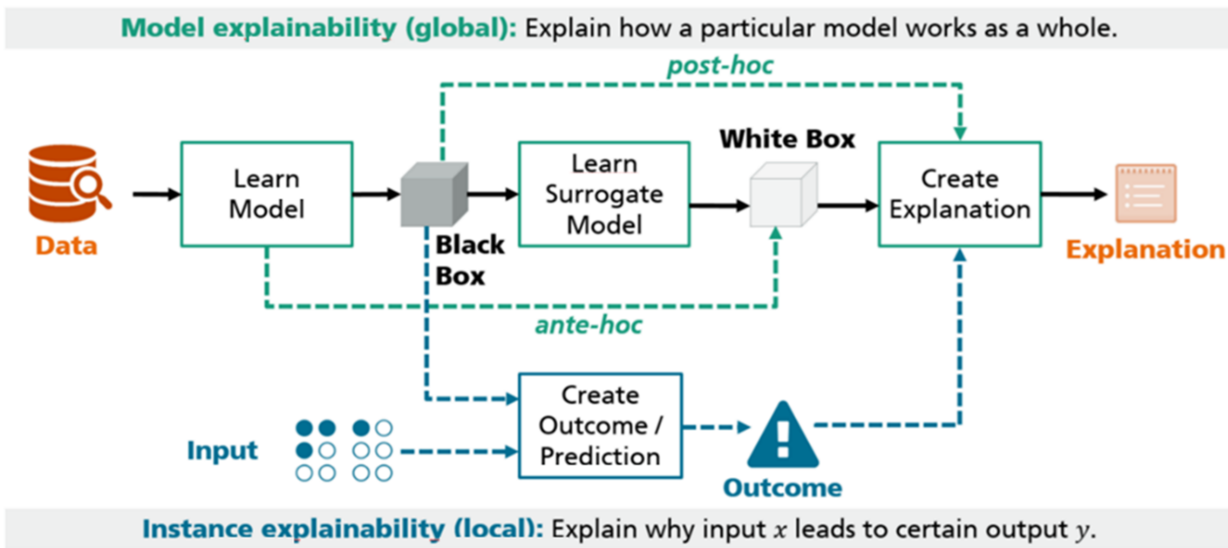

Figure 53. Different ways of explaining a black-box machine learning model

(2) *Model explanations:* here, a black-box model is used and XAI is used to explain the model as a whole. There are two approaches; 1) *post-hoc model explanations,* which take the black-box model as is and provide model insights afterwards and is usually model agnostic, i.e., it works for different kinds of machine learning models. Famous examples of post-hoc explanations are partial dependency plots (Friedman, 2001), which show the relation of one or two input features to the model's outcome, or feature importance values. 2) Surrogate approaches (Schaaf et al., 2019) involve learning a white-box model in addition to the black-box model, where the white-box model is used to explain the outcomes of the black-box model. Common surrogates are decision trees or rule-based systems.

(3) *Instance explanations:* in contrast to model explanations, so-called instance or local explanation methods do not explain the whole model. Instead, explanations for individual data instances are provided. A famous representative of the instance explanation methods are saliency maps, which are often applied for image data. Here, the image is overlaid with a heatmap that is highlighting those parts of the image that contribute most or least to the outcome of the black-box machine learning model. Other often-applied methods are SHAP (Lundberg & Lee, 2017) and LIME (Ribeiro et al., 2016).

In safety-critical domains like human-robot collaboration, where machine learning models may only be applied after some rigorous verification step, surrogate models form a promising subfield of XAI. In (Bastani et al., 2018) it has been shown that it is possible to extract a verifiable surrogate model based on a decision tree from a black-box neural network control policy. Closely related to XAI research field are uncertainty quantification methods (Abdar et al., 2021) and physics-informed machine learning (Vonrueden et al., 2019).

Uncertainty quantification aims at providing information about the reliability or certainty of the machine learning model's outcome. There are two sources of uncertainty in machine learning in general: *aleatoric* uncertainty refers to the variation of the model's outcome due to random effects, while *epistemic* uncertainty is caused by a lack of knowledge. To reflect the uncertainty of the model's outcome, often Bayesian learning, and inference methods are used, where the outcome is no longer a point estimate but a random variable. In *physics-informed machine learning*, one tries to enrich the purely data-driven learning approach with prior information or domain knowledge, which might be available in form of algebraic equations, physical laws, simulation models or logical rules. When combing the resulting model is often called a *gray-box*, which is not fully transparent to the human, but at least some parts of the model are comprehensible. Informed machine learning allows addressing one major weak point of machine learning, which is its weak extrapolation behavior. That is, the model only provides reliable outcomes for input data that is well represented in the training data. If the input is outside the distribution of the training data, the model may behave arbitrary and is no longer trustworthy.

5.8 Regulatory framework for AI in manufacturing

The integration of AI with manufacturing technologies and systems is expected to allow mid- and long-term competitiveness and welfare for Europe. Currently, the blend of a number of general frameworks, developed standards and ethical regulations are used as the foundation for AI assets development, where the objective is typically to produce trustworthy AI in the sense of legal, ethical, and robust modules. Regulatory frameworks that deal with a series of AI relevant aspects include among others the General Data Protection Regulation (GDPR), e-Privacy Directive, Electronic Communications Framework, and the Regulatory framework proposal on artificial intelligence[38]. Yet, the absence of specific regulations and standards for AI components and the low understanding of the algorithms and processes among key stakeholders may create critical challenges and complications hampering the broad adoption of AI. For instance, the lack of broad specificity on the regulatory landscape leads to gaps between the defined principles and their translation into practical requirements and development actions. In this context, the next paragraphs discuss several articles of the Regulatory framework proposal on artificial intelligence and their implications for industrial practice.

5.8.1 Article 5: Prohibited artificial intelligence practices

Article 5 sets out a list of prohibited AI practices. This list includes for instance the development of AI systems that can cause physical or psychological harm to individuals, and result in discrimination against individuals or groups of individuals on the grounds of age, physical or mental disability. Subsequently, the application of Article 5 will be discussed for the case of hybrid production systems. As a starting point, hybrid systems including robots and other AI-controlled machinery can be considered high-risk systems.

[38] https://digital-strategy.ec.europa.eu/en/policies/regulatory-framework-ai

Therefore, formal risk assessment methods are needed to prevent the potential implications of AI stochasticity. AI is being researched to bridge the human and AI systems worlds, i.e., to enable smart reactions from machines, but also the implementation of efficient and usable means of human machine interaction. The collection of data related to human status, intentions, and preferences is needed to adjust the robot and machinery behavior accordingly, and on the other hand humans need interfaces providing them with the required did and information while optimizing cognitive effort. Special care must be taken to ensure fundamental prohibitions outlined by EU legislation are taken into account and formally applied, including restrictions on direct physical or psychological harm, but also the avoidance of subliminal techniques for manipulating human judgment, preventing exploitation of personal vulnerabilities, and promoting inclusion of people with disabilities. Since in many cases the optimization of the individual user experience relies on their identification, profiling or social scoring, methods that can guarantee the elimination of the prohibited practices need to be employed.

5.8.2 Article 9: Risk management system

Article 9 of the proposed regulation on artificial intelligence focuses on risk management systems for AI. This means that AI developers need to implement risk management systems to assess and manage risks posed by AI systems in order to minimize the risks posed to individuals, the environment, but also the public interest. Risk assessments are already performed in current industrial practice, where experts are engaged to perform risk assessment of new machinery introduced into factories focusing especially on potential risks imposed due to the particular new machinery. Assuming that the amount of AI tools to be introduced to the factories of tomorrow is expected to rise dramatically, a *new set of approaches for running risk assessment* is required. The conduction of regular risk assessments, the development of risk mitigation strategies, the monitoring of AI systems to detect and timely respond to potential risks, the consideration of cyber security risks together with regularly updating the risk management system and providing training to the users of AI systems are key actions that derive from Article 9. Several of these processes need to be standardized and automated, supported largely by *software tools* that can perform a large part of the process and thus reducing cost and time.

Potential risks in AI that are relevant to the manufacturing sector include but are not limited to the mismatch of models and reality, incomplete testing and/or verification of the AI modules, bias, incomplete definition of data for training, inadequate selection of performance measures and metrics, high error rate, as well as selection of incorrect objective functions. Consequently, strategies to prevent such risks, detect the occurrence of unwanted behaviors, as well as countermeasures to eliminate or restrict the consequences of the risks occurrence should be defined. This process should be supplemented by incorporating methods for *workforce training and upskilling* on how to use the AI enhanced machinery and tools. The factory personnel need to be adequately educated in order to reduce the risk of misuse and the compliance of the usage to the intended purpose of the AI system.

5.8.3 Article 10: Data and data governance

Article 10 refers to data, data governance, and management practices including data collection, data preparation processing operations (annotation, labeling, cleaning, aggregation, etc.). Although there is a plethora of AI applications developed for the manufacturing industry, training of data sets based on data coming from the manufacturing industry is rather lacking today. Several factory applications being developed are making use of models trained by non-factory datasets making them unsuitable for the purpose. Therefore, a new range of trained models is required. For that objective to take place, data management and governance that would be suitable for the practices of manufacturing industry is required. The requirements range depending on the size and nature of manufacturing company and different approaches need to be piloted and investigated in practice. Ensuring that data sets come structured and free of errors structured based on well-defined formulations and assumptions can help to increase dramatically the acceptance by industry in sharing data and thus develop mature models fit for the purpose. Research on **tools for rapid creation of datasets, as well as initiatives where businesses share datasets on European level should be encouraged.**

5.8.4 Article 11: Technical documentation - Article 12: Record-keeping – Article 18: Obligation to draw up technical documentation

Technical documentation of high-risk AI systems should be present, to ensure correct integration and usage of such systems by experienced or unexperienced personnel. Structured technical documentation as well as instructions should be delivered and made available via interactive and easy to use mechanisms, such as dedicated platforms, that may also serve training purposes.

Considering the complexity of AI based systems with regards to the aspects of keeping track of records, a broad set of new requirements is emerging on that article. High risk AI providers have to consider logging data and release software updates throughout product's lifecycle. Also, high risk AI recalls need to take place IF log data prove incapability to conform on technical directives. Deeper investigation is required on structuring approaches for keeping records on how AI systems have been trained, possible decisions they may have made, false or true positives and several other aspects in correlation with the actual manufacturing process that has been controlled. Special attention needs to be paid on aspects of manufacturing shop floor conditions, machinery, configuration of production line, product characteristics, materials properties at the time of decision making. A broad set of investigations is required to help structure properly a reliable record keeping approach. The challenge becomes greater when expanding to the engineering and management decision making, which entails a large number of heterogeneous data formats that are used per production step. The advances in CAx tools have facilitated the use of AI algorithms in several product/process life cycle stages such as design, planning, scheduling, etc., which cannot be neglected when considering documentation and record keeping aspects. However, the large amount of heterogeneous data makes the link of consecutive steps and the identification of the sources of error hard to identify. An effort to enhance traceability and facilitate record-keeping is launched through creating Digital Threads connecting modules that are used in engineering, production, and management, as well as the use of neutral data formats to link the produced information to the engineering software that was used to produce it.

5.8.5 Article 13: Transparency and provision of information to users

Aspects of transparency in the process of decision making are deemed to be critical in factory operations planning and control aiming to help interpret systems' output. A broad range of factors influencing the way the AI system performs need to be considered and studied, for example data structures, data formats, data accessibility, quality of training data and quality of operating data, condition of machinery, sensors and actuators and several other aspects that need to be evaluated carefully and in a structured and coordinated manner. **Graphical interfaces depicting a) what dataset or Neural Networks parameters are affecting the results, b) what changes training causes and on which extent, and c) what is the system's objective during unsupervised training are needed.**

5.8.6 Article 14: Human oversight

Designing and developing human-machine interaction tools has been traditionally a key feature of charactering technology. However, with the emergence of AI technology, these tools need to be radically reconsidered at all stages of the manufacturing lifecycle helping people to manage both the variety of data as well as the evolution of AI modules over time. Human oversight is expected to be rather challenging area to regulate due to the direct involvement of people, different people profiles and levels of training, education, age as well as the broad range of manufacturing and machinery related particularities such as parameters and variables to model and link to AI decision making logic. GDPR and legal rights require several technology considerations to be efficiently applied considering factory planning and operations both at the shop floor as well as the supply chain and customer interaction levels.

The design of the AI systems directly affects the performance of humans when overseeing the system's operation. Especially when intelligent manufacturing systems are designed based on techno-centered approaches and involve human operators to only handle difficult situations or require quick reactions to correct system's failures, the human oversight becomes harder. Research effort should be oriented towards human-centric design of the operators' role to cover for system design deficiencies that result from the neglection of the operators' expectations, capabilities, characteristics, and limitations including situation awareness, interpretation of visual input, anomaly detection, decision-making, but also the level of trust to automation.

The trust in automation is linked with the ability of operators to interpret the system's decision-making. The AI tools have been considered in the past as "black boxes". This has been acting as a barrier for the industrial users to adopt such technologies in their manufacturing system. On this basis, appropriate human-AI system interfaces need to be designed and implemented allowing the factory personnel to interact with the AI tools. New methods that enable the *explainability* of the AI decision-making systems can be integrated in intuitive interfaces. These should provide the involved human operator with the ability to: a) monitor the operation of the AI tools through structured visualizations, b) identify/estimate errors or unexpected outcomes, c) encapsulate her/his experience in the decision-making process, d) intervene to / bypass the output decision in case this is considered in appropriate.

5.8.7 Article 15: Accuracy, robustness and cybersecurity

Article 15 discusses the aspects of accuracy or business in cybersecurity related to high-risk AI systems. The robustness and accuracy of an AI system are significantly affected by the algorithm development phase and the training data which are utilized to initiate and train the system. Accordingly, efficient methodologies to evaluate the accuracy of an AI system during its utilization are required. The evaluation could be based on prognostics able to estimate a set of specific KPIs relevant to the AI system accuracy and robustness. The evaluation may investigate the performance of all the components of the AI system (models, data structures and others) aiming to estimate the level of uncertainty/inaccuracy for each one and how they affect accuracy of the complete system. Besides accuracy, cybersecurity should also be considered with the development of dedicated modules protecting middlewares and datasets from "poisoning". An approach could be the use of independent networks and processing units running in parallel **with at least, one processing unit being isolated from the factory's network during normal operation.** Both processing results should be compared and in case differences that exceed particular thresholds are detected, then safety functions should be triggered**. On top of that, f**unctional safety norms for AI systems should be developed, meaning that the AI modules will actively prevent the failure of the whole system or the causing of harm to people and property in case of error/ violation/ damage.

5.8.8 Article 16: Obligations of providers of high-risk AI systems

The definition of high-risk AI systems involves such technologies that have access to personal data, are connected to critical infrastructures, law enforcement, border control and other public or administration services. In the manufacturing landscape, this can be related mainly to the safety-related hardware and the decisions taken based on its signals. The provider of such AI-based components should ensure that the safety systems would work in a timely manner, assuring the human safety under any circumstance. At the same time, the AI-based safety components should be able to understand the human activity and intention, avoiding unnecessary drops in the production rate or even stoppages by random human activity that is not related to the production and, of course, doesn't impose any safety risk to the human operator.

5.8.9 Article 17: Quality management system

Quality management is a key aspect in manufacturing in terms of providing products of certain standards and remaining competitive in a continuously changing market. The AI-based systems which can be deployed inside the spectrum of quality, will be based on the use of data deriving from multiple manufacturing resources involving in many cases the human factor. Strategies shall be proposed in order to ensure that the integration of data sources will comply with the EU and national regulations. Examinations/validations have to be undertaken in order to ensure a safe and unbiased use of the provided technologies. The accuracy of the AI-based systems should be monitored easily through interactive tools upon deployment. The degree and velocity of self-learning for the AI-based systems shall be in-depth documented and validated in real-case scenarios of industrial requalification. In addition, the systems' impact on humans should be examined focusing on aspects such as operational managerial decision-making in quality-related issues. After-market monitoring should be encouraged taking into account customer report/incidents and correlating them with industrial malfunctions from different levels of abstraction.

5.8.10 Article 20 Automatically generated logs

Log files help the programmers identify system status and detect potential errors or warnings that occur. Similar, AI-based systems should keep such logs and help the programmers understand how the AI algorithm has worked during both the training period and the execution period. Also, the algorithm when categorizing the different datasets, should require human assistance to ensure the proper classification. Lastly, the AI algorithms should be trained to recognize keywords from the logs helping themselves identify issues that may occur or ensure that they are running as expected. Especially in the cases of high-risk AI systems, logging plays an important role to identify unexpected hazards.

5.8.11 Article 21 Corrective actions

In relation to Article 20, once unexpected activity is logged in the system, corrective actions should be taken, ideally by the AI system itself, depending on the severity of the error and its category, i.e., if it is a production error or a human operator safety error. If the error has a higher level of severity and cannot be automatically handled, then the programmer should intervene and take the necessary corrective measures to help the system overcome it. If the error is simpler and corrective actions can be automatically applied by the AI-algorithm itself, then the necessary messages should be logged to inform the programmers and the system should proceed without any interruption. Corrective actions also include keeping the AC system distributors posted on the deviations of the systems regarding the expected behavior in order to advise the end user when it is needed to perform actions to bring the system into conformity, to withdraw the system or recall it.

5.8.12 Article 22: Duty of information

The automatically logging system, described in article 20, as well as the corrective actions, should be shared with all the necessary actors of the production chain. This also includes the programmers and/or the integrators of the AI system in the production lines to help them improve the future algorithms.

5.8.13 Article 29 Obligations of users of high-risk AI systems

When integrating AI decision making tools and / or AI enhanced machinery in the manufacturing value chain, it is critical to ensure its appropriate usage from the involved personnel. Dedicated training platforms should be created, comprising of a variety of training mechanisms, such as user manuals, visual in the form of presentations and videos, online and on-site training sessions. A closed loop between the technology provider and the industrial users can be established allowing the latter to report back any identified malfunctions, unexpected incidents during the usage of the AI tools. The industrial workforce needs to be well educated in the definition of the proper data types and amount needed as input to the AI decision making tools to ensure the proper usage and exploitation of the AI systems' capabilities.

Therefore, the existing regulatory frameworks should be extended and further developed to support the implementation of synchronized standardization activities on AI and related digital technologies in manufacturing in member state, European, and global levels. Standardization and international collaboration are indispensable to support the AI solutions deployment.

5.9 Consolidation of AI application for cross-cutting aspects in manufacturing

As presented in previous sections, AI modules are currently dedicated on specific product/production stages and digital processes are implemented in silos. AI should be integrated in multi-processes covering the complete lifecycle. An end-to-end Digital Twin enabling to share product-process-resources data among design, engineering, management, and production agents would increase responsiveness, effectiveness, and precision and at the same time minimize design and engineering iterations. This will be achieved by the implementation of a framework to integrate data models, data-driven algorithms, and digital twins of assets and products enabling the continuous update of the parameters of digital models according to production feedback. Cross-correlation between simulation data, process monitoring and quality control will provide knowledge on the process that will be translated into process models updates. Figure 54 is an extension of Figure 6 enhanced with data and information flows that can act as feedback loop to the applications of previous stages of the product/process lifecycle, which illustrates the described concept.

Nevertheless, the implementation of the Digital Twin is accompanied with requirements on data collection, processing, exchange, and storage. Connectivity should be ensured despite the different data sources (CAD, CAM, CAE and CAPP software, quality control reports, sensor data etc.) and the heterogeneous data formats (text, images, audio, CAD files, etc.). Common semantic models describing the manufacturing processes can enable connectivity and integration of the different manufacturing instances. In particular, linking of the product, process, material, and metrology models can be enhanced by using neutral formats such as STEP (product design), PSL (Process Specification Language, manufacturing processes), and QIF (Quality Information Framework, dimensional measuring). AutomationML can support modelling and data exchange among the several different engineering tools.

Furthermore, metamodels should be developed for data indexing to facilitate data access and traceability. At the same time, developers should ensure data integrity, security, but also clearly define access rights by humans or software.

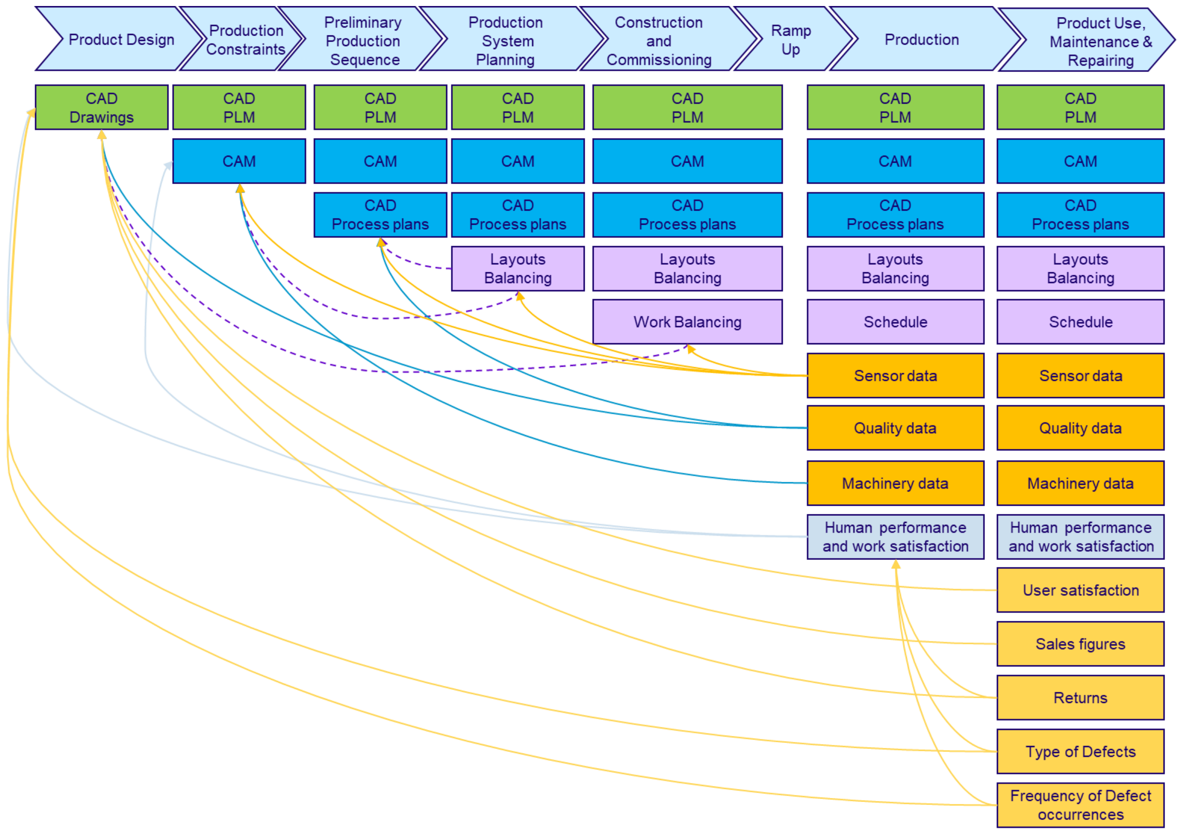

Figure 54. Data connectivity, data access and sharing among data models in the digital twin

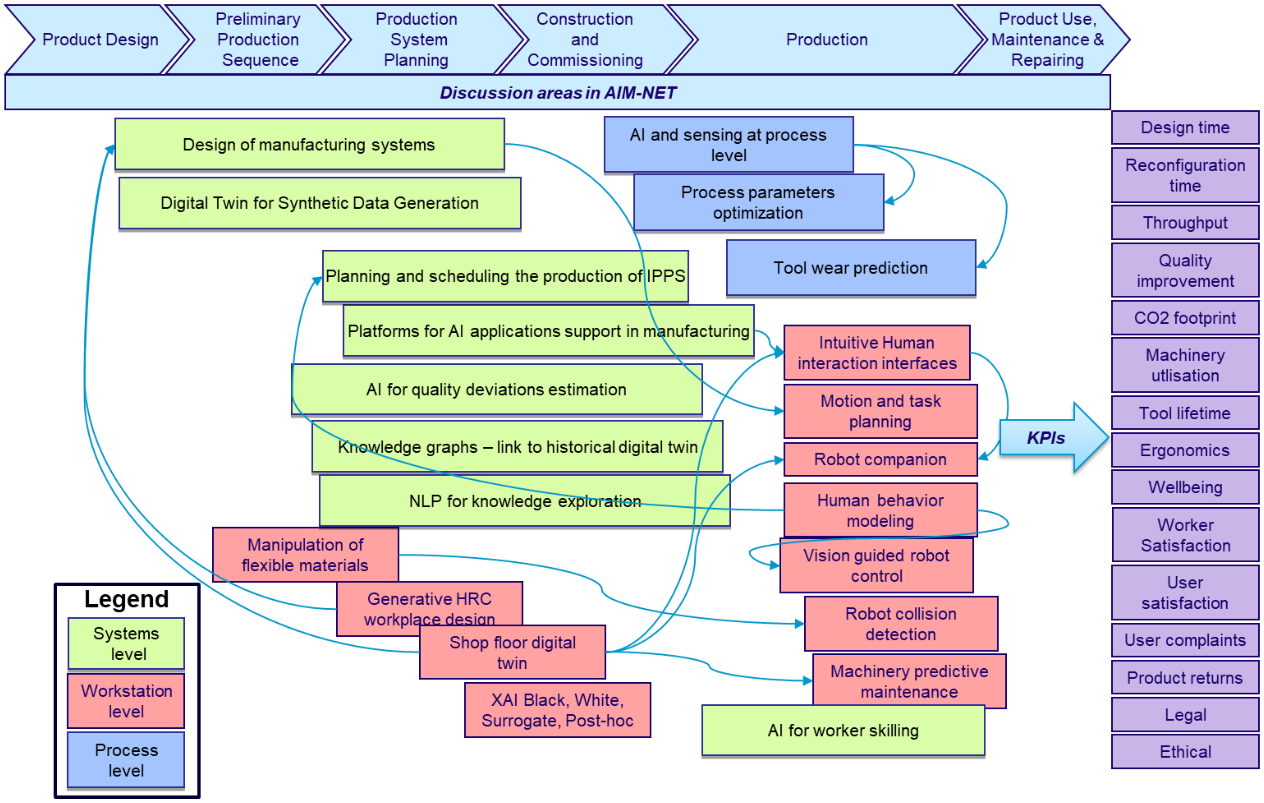

Figure 55. Pluggable and connectable AI modules concept

Figure 55 is based on Figure 5 enhanced with the visualization of beneficial modules interactions and exchange of information which can improve the performance of the AI-based solutions, especially in the case of non-symbolic AI, by enabling access to more data that can be used for modules' training. Enabling the communication between the AI modules can provide several benefits, especially when the data integrity, cleanliness, and wealth are not ensured. The data exchange between the modules can be utilized among others for ensuring the 1. quick training of AI modules e.g., data and information from the shopfloor's digital twin can speed up the training of machinery predictive maintenance 2. quality-by-design by providing data from the production to the engineering, 3. cross-correlation between data gathering from simulation, process monitoring and quality control for acquiring knowledge and updating process models, 4. evaluation of models for any non-accepted parameter values in real-time, and 5. self-adaptive online control to correct deviations. To this end, modular system architectures should be adopted including interfaces for data exchange, while handling the connectivity with different digital manufacturing ecosystems (e.g., Mindsphere, Teamcenter, Azure), enabling the communication between new and legacy systems, but also between proprietary and open-standards. This can be achieved by implementing connectors and mediators such as IoT gateways, context brokers. In turn, this would require an integration interface (lightweight middleware such as ROS, MQTT, EtherCAT, etc.) for orchestration, vertical integration and storage of manufacturing and product data. Also, the OPC UA protocol can promote seamless and secure communication among manufacturing assets and modules.

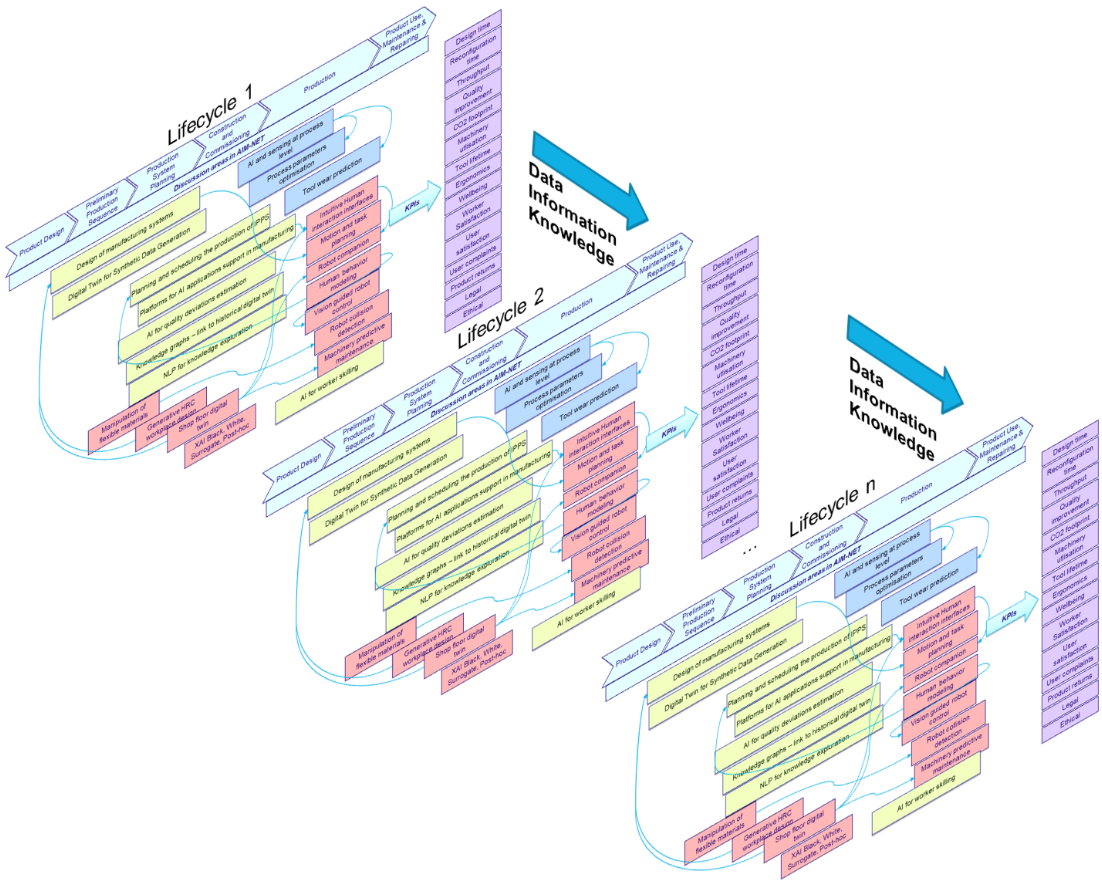

Figure 56. Adaptive AI modules concept over the lifecycle of the product

Aside from exchanging data among several stages of one product variant's lifecycle, it is worth investigating the exploitation of data from previous product variants. Focusing on the AI modules level, the use of the already existing data along with strategies for synthetic data generation and learning methodologies can contribute into enabling the adaptability of the AI modules i.e. the ability of the module to adapt to different scenarios, requirements, and constraints. Optimization will be performed from variant to variant by altering model, simulation, control, etc. parameters over time aiming to improve performance against the relevant KPIs e.g., cost, flexibility, time, quality. This will require to define data models that will remain relevant over time, strategies for maintaining and updating data models, as well as for data storage.

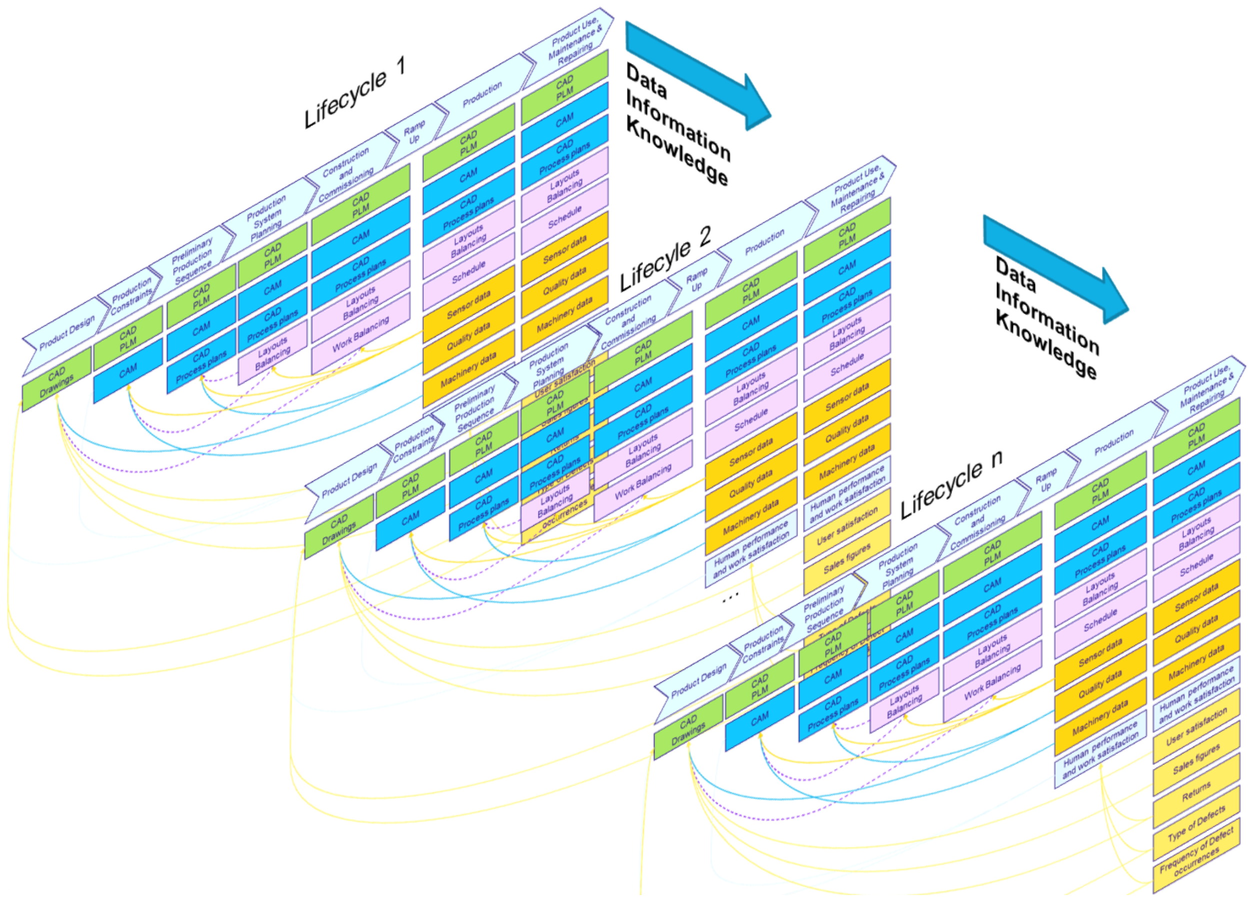

Figure 57. Optimization of the product lifecycle

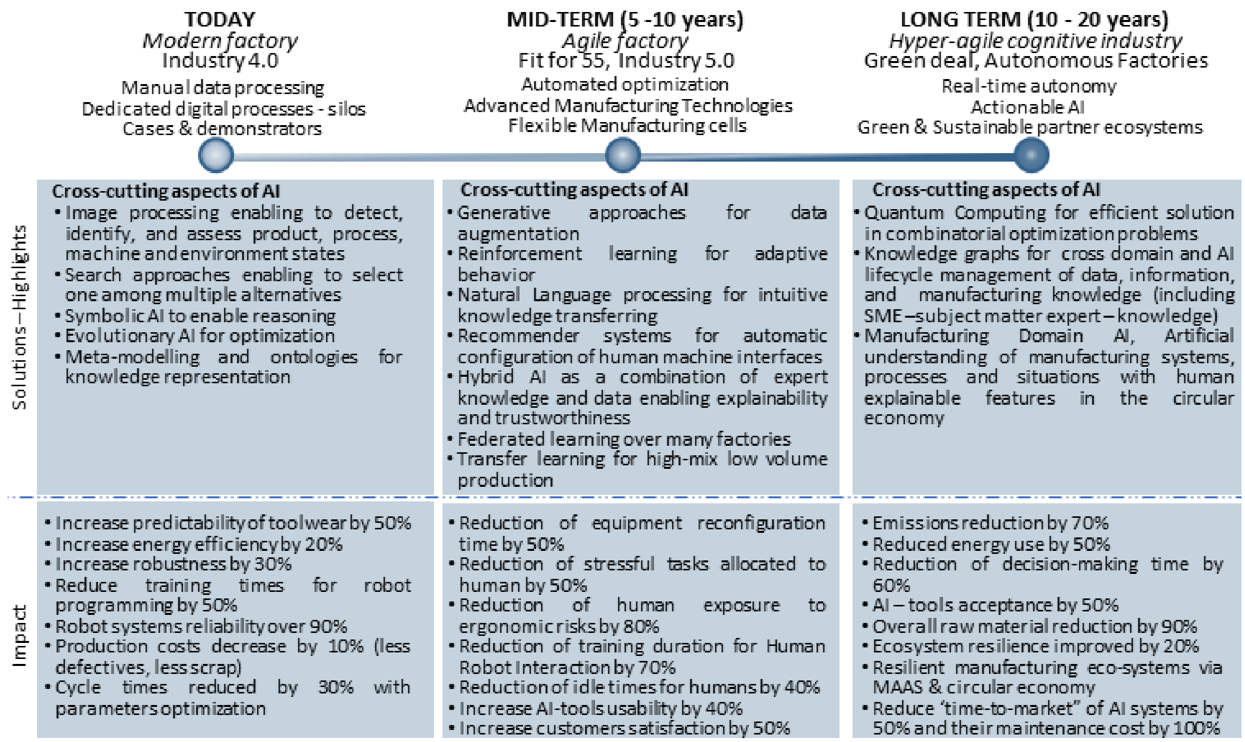

Figure 58. Current status and Future Vision for the adoption of AI at the Manufacturing level

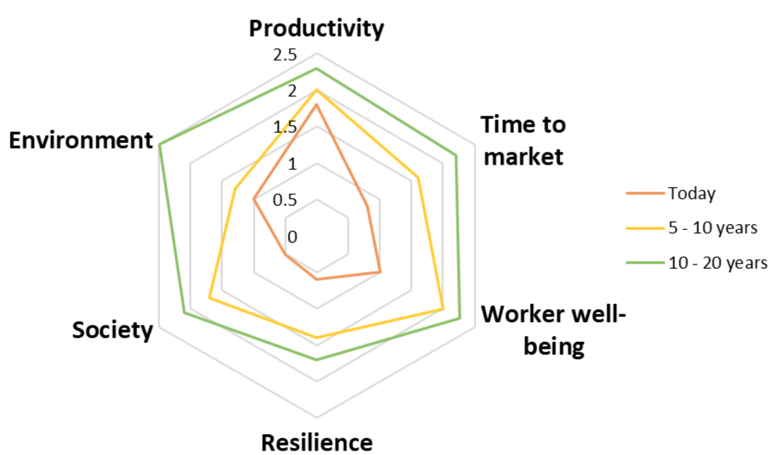

Figure 59. Degree of vision achievement

XAI is a relatively young research area, but it has the potential to be a key driver to support the integration and adoption of AI approaches in industrial robotics. However, XAI faces some open challenges. For instance, choosing the most appropriate XAI approach for the problem at hand is often not systematic. A standard procedure is missing that allows measuring, quantifying and comparing the performance of different XAI methods. From the algorithmic side, surrogate models are a promising approach when verification and safety are paramount. However, the quality and fit of surrogate models is currently not increasing with the same pace as the representational power of deep neural networks. The main constraint that has been reported is the computation time that is needed, especially for automated planning and reasoning. A solution to this challenge could be the use of quantum computing.

Quantum computing is an emerging computing paradigm that seems promising towards supporting complex computations. One of the most well-known examples is the seminal algorithm developed by Peter Shor (Shor, 1999), which allows to efficiently factor prime numbers which is a substantial speed-up compared to the best-known classical alternative which requires a super-polynomial runtime. While the early excitement around quantum computing was primarily driven by theoretical considerations, the technology has received an increased interest that is fueled by technological and scientific breakthroughs such as the first experimental demonstration of quantum supremacy (Arute et al., 2019) and the increasing availability of cloud-accessible quantum computers. Nevertheless, quantum computing is a relatively young technology that has only recently made the transition from purely fundamental research to potential applications.

The current application of quantum computing is thus often limited by the technological development of the hardware. Due to the nature of quantum systems, any kind of interaction with the external world, e.g. for state manipulation or read-out, necessarily results in the disturbance of the system which in turn results in noisy calculations. If the noise is beneath a certain threshold, error correction codes can be implemented which allow for fault-tolerant computations. This, however, requires substantial technological advances with results expected on the timescale of several years (Gambetta, 2020). Currently, the field is mostly concerned with either improving conventional machine learning algorithms with quantum computing or with adapting known concepts to quantum systems. Among the most prominent methods are quantum neural networks and kernel methods. The first term subsumes a diverse class of algorithms whose main commonality is that they have a layer-wise structure which is trained variationally using a classical computer. Although promising results hint at potential exponential speed-ups (Liu et al., 2021) , finding useful kernels which can efficiently be calculated using a quantum computer while being hard for classical computers is an ongoing research question. The applications for quantum machine learning in manufacturing are very similar to conventional machine learning methods and include problems like quality assurance, anomaly detection or predictive maintenance. One of the most critical active research topics, which is expected to remain one of the most important research questions in the upcoming years, is to find relevant industrial use-cases where the possible speed-ups can be translated into a real advantage. As a next step, quantum computing is expected to be applied to complex optimization problems such as materials and process design. From the manufacturing perspective it will be very interesting when quantum computing will be used for designing the materials-manufacturing cycle so that one can design totally new materials, structures, and processes in order to get the optimized component or product from the life-cycle perspective. Also, quantum computing will be a breakthrough technology for cybersecurity which will concern also manufacturing industries.

Another interesting topic is the robustness of the AI solutions, as there is high temporal uncertainty in the manufacturing systems that causes drifting of prediction models, which in turn invites for developing methods for self-evolution of prediction models. On top of that, the dynamic conditions of manufacturing systems at all the discussed levels would be highly favoured by the development of self-configurable algorithms. Furthermore, the incorporation of expert knowledge is of high importance for manufacturers as retaining worker specific knowledge is valuable to ensure product quality, responsiveness to production deviations, and explainable reasoning for decisions made automatically.

6 Conclusions

European industry has made significant progress in adopting Artificial Intelligence technologies in recent years. AI has become a key driver of innovation and competitiveness for EU industries, and many companies are investing in research and development to explore new applications for AI. As an overview AI has enabled us to improve the engineering, execution, and monitoring of manufacturing processes, the ergonomics of operators but also overall their well-being. In detail, AI-empowered tools have relieved operators from physical and mental discomfort through the enabling of human robot collaboration, the implementation of smart exoskeletons, as well as wearables and interfaces that enrich the operators' situational awareness, support memory demanding operations, and assist decision making. Furthermore, solutions have been provided to cover the design, engineering, and operation of the manufacturing systems, including the design of production lines, work management, knowledge transferring, as well as optimization of operations' planning. Several technical problems have been dealt with already from the early period of AI emergence, whereas others such as explainable, ethical, and responsible AI belong to the list of emerging research topics. The achieved results that are gathered in Figure 60 seem promising, however, there is a number of open issues for fulfilling industrial expectations.

The deployment of AI solutions validated in laboratories, relevant industrial environments, or on the shopfloor has helped to identify shortcomings of the AI-based methodologies and algorithms. The common conclusion is that despite the significant progress of the research community, and the promising results that have been accomplished, more effort is needed until AI solutions can be trusted and widely adopted by industry. In more detail, it is needed to address a list of barriers that have been identified. One amongst the most critical barriers has been data collection. This aspect is linked with both technical challenges such as the selection of data to be collected, managing the large volume of data, selecting the means for data collection, cleaning and pre-processing of data, as well as selecting data formats, digital platforms, and communication standards to be used. At the same time, there are more and more concerns about privacy, security, inclusiveness, equity, traceability, and data governance. Moreover, the upgrade of legacy equipment to support the implementation of AI solutions is deemed one of the most interesting topics, as acquiring new equipment with advanced sensory capabilities is usually not economically feasible considering that legacy machines are functional. On the other hand, the upgrade of legacy machines is typically accompanied by extra fees and licenses to machine providers for integrating updates towards machine digitalization, discouraging the adoption of the emerging AI solutions. As a result, research on IT infrastructures supporting the management of data, the implementation of interoperable digital pipelines, digital twins, and standardized integration of data processing and AI modules is needed.

Another point that has occurred is the application of AI in multiple processes instead of applying AI dedicated to process steps in support of process optimization towards zero defect manufacturing, sustainability, and minimization of environmental the impact of manufacturing systems. This is also connected to the implementation of intelligent machines and the time needed for programming and commissioning of new robotic applications for flexible and resilient production. This has motivated AI research to exploit feedback coming from the process (e.g. cutting) parameters to avoid scrap, material and time waste, but also the need for reworks. In the same view and given the strategic goal to achieve climate neutral manufacturing, researchers have provided a number of models predicting and optimizing machinery operation for the reduction of energy consumption.

	TODAY *Modern factory* Industry 4.0 • Manual data processing • Dedicated digital processes - silos • Cases & demonstrators	MID-TERM (5 -10 years) *Agile factory* Fit for 55, Industry 5.0 • Automated optimization • Advanced Manufacturing Technologies • Flexible Manufacturing cells	LONG TERM (10 - 20 years) *Hyper-agile cognitive industry* *Green deal,* Autonomous Factories • Real-time autonomy • Actionable AI • Green & Sustainable ecosystems
Solutions – Highlights	**Manufacturing Process level** •Multi-sensor quality monitoring •Automated process quality assessment •Tool wear assessment •Process parameters optimization	**Manufacturing Process level** •Generative design of process plans & materials •Process control under uncertainty •Tool wear prediction& predictive quality •Explainable AI suggestions during root cause analysis •Adaptive generation of process models	**Manufacturing Process level** •Zero-Defect manufacturing •Automatic alarms management •Predictive control
	Workstation level •Automated generation of workplace layout & task allocation •Dynamic task planning & coordination •Precise and robust robot manipulation •Intuitive robot programming •Dynamic and context aware operator support •Condition monitoring based maintenance	**Workstation level** •Seamless Human-Robot Collaboration •Task planning under uncertainty •Robot behavior adaptation based on human preferences •Robots as adaptive fixtures •Robot and machines status and behaviour prediction •Composition and configuration of machining skills	**Workstation level** •Human-Robot Social interaction •Robots with decision autonomy •Robot self-adaptation based on human intention and needs •Self-evolution of machine status prediction models •Self-optimization of overall task set related to internal and external requirements
	Manufacturing System level •Automated generation and evaluation of production lines • Multi-criteria resource planning	**Manufacturing System level** •Automated reconfiguration of production lines •Trustworthy smart manufacturing via Digital Twin-based platforms •Shared economy with automatic mapping of products and resources	**Manufacturing System level** •Self configuration of production lines & manufacturing eco-systems, e.g. automated supply chains management •Smart work management based on human skills, expertise, and preference •Operational Safety and Resilience Intelligence
	Cross-cutting aspects of AI •Image processing enabling to detect, identify, and assess product, process, machine and environment states •Search approaches enabling to select one among multiple alternatives •Symbolic AI to enable reasoning •Evolutionary AI for optimization •Meta-modelling and ontologies for knowledge representation	**Cross-cutting aspects of AI** •Generative approaches for data augmentation •Reinforcement learning for adaptive behavior •Natural Language processing for intuitive knowledge transferring and robot commanding •Recommender systems for automatic configuration of human machine interfaces •Hybrid AI as a combination of expert knowledge and data enabling explainability and trustworthiness •Federated learning over many factories	**Cross-cutting aspects of AI** •Quantum Computing •Knowledge graphs for cross domain and AI lifecycle management of data, information, and manufacturing knowledge Manufacturing data spaces and digital passports •Manufacturing Domain AI, Artificial understanding of manufacturing systems, processes and situations with human explainable features in the circular economy
Impact	•Improvement of energy efficiency by 15% •Increase the capturing of AI potential by adopter companies to 10% •Improvement of workplace ergonomics by 20% •Increase defect predictability by 15% •Reduce robot programming time by 40% •Robot systems reliability over 80% •Automation of root cause identification by up to 40% •Real-time quality monitoring at 50% of products	•Reduction of energy use by 30% •Reduction of GHG emissions from industry between 18.2 to 25.1% •Increase the workforce that has basic digital skills to 70% •Reduction of training duration for Human Robot Interaction by 70% •Improvement of resource utilization by 40% •Increase of the AI adoption rate by 25% •Reduction of 'time-to-market' of AI systems by 20% and their maintenance cost by 30%	•Climate neutral manufacturing •Reduction of decision-making time by 60% •Overall raw material reduction by 90% •Improvement of ecosystem resilience by 20% •Enhance resilient manufacturing eco-systems via MAAS & circular economy •Reduction of 'time-to-market" of AI systems by 50% and their maintenance cost by 100%

Figure 60: Roadmap for AI R&D activities

Besides technical factors, AI has the potential of significantly improving the everyday life of the humans involved in manufacturing systems. To this end, it is important to provide tools for accessible visualization of data regardless of the humans' background, mother tongue, gender, sight, hearing and other capabilities. It is important for technology acceptance to not only simplify the interaction of operators, engineers, managers, and the rest of the manufacturing stakeholders with data, but also to ensure that the derivation of the results is explainable. Ontologies, mental models, and data semantics are the backbone of these solutions, so it is expected to remain relevant for the years to come. Additionally, it is worth developing solutions for the personalization of data visualization beyond dashboards because this may improve the understanding and situational awareness of individuals and thus improve productivity, efficiency, and at the same time prevent process and/or automation failures due to human error. Also, it is possible that research on AI for decision support significantly reduces stress that is needed due to making decisions, needing to memorize large sequences of operations, extended catalogs of products, complex processes, and the location of several resources on the shop floor.

Another barrier is the affordability of AI solutions considering the limited availability of financial resources for investments in technology, which are even more restricted in the case of SMEs. Due to the capital-intensive nature of innovative technologies and the risk aversion mentality of the manufacturing sector, unwillingness among companies to adopt new processes is often. Therefore, adopting digital based processes is perceived as a risky step, due to the lack of relevant published case studies and industrial secrecy of early adopters. promoting success stories through key market leaders releasing relevant technology information, benchmarking and assessment for further replication.

It seems that in the next years SMEs will rely on interoperable solutions and data-exchange formats, aligned with industry initiatives. On the other hand, since the adoption of new production technologies requires massive knowledge acquisition (staff and operators) and trustiness methodologies addressing these issues are expected to flourish in the next years, whilst education and attraction of new talents will also be enhanced even in the context of coordinated regional ecosystems. Moreover, methodologies for the valorization of AI are needed.

In the future the integration of AI solutions is expected to be facilitated by enabling deployable AI units. Researchers are working on simplifying the generalization of AI solutions, which will be the foundation of deployable AI units together with the faster automated modelling of the environment, processes, human behaviour, parts, etc., but also the simplification of multi-process modelling. Effort is also needed to produce methodologies that will guide end-user into selecting the right AI tool for their case. For instance, methods to "Design for AI", reduce the complexity of scaling up, as well as facilitate AI-based solutions acceptance and develop hybrid skills are needed. Additionally, methods to ensure agile development, safety, privacy preservation, reproducibility,

Additionally, the manufacturers need evidence of profit before investing, as well as assessments of their competitiveness if they adopt AI solutions. Another key factor regarding the AI approach to be deployed has to do with its acceptance and natural integration in the manufacturing ecosystem. The AI solution should strongly support human interaction with the learning and reasoning process. As a consequence, the explainability of the deployed AI and the interpretability of recommendations made must be assured. In the case of human-robot collaboration and automation, the capability to predict human behavior can crucially improve the usability, efficiency, effectiveness, and proper trust and confidence to the designed systems. Proper human behavior modelling is expected to pave the way for the transition from the contemporary solutions that are dealt with reluctancy due to the expected cycle times to highly efficient, seamless, and safe human robot collaboration, reaching even the level of social human-robot interaction. In addition to that, the accurate and real-time perception of the robot's surroundings can improve the so far achieved results in HRC in tandem with the enabling of resource aware dependable behaviors and also increase the reliability of robotics solutions. Focusing on machinery related aspects, it is expected that perception will be enhanced, for instance enabling the fast training of AI algorithms for new product variants, for wider ranges of ambient conditions (lighting, etc.), backgrounds, and with extended tolerance to electromagnetic noise.

Moreover, there is yet effort to be made on identifying, implementing, and promoting the adoption of new education processes. On top of that, the community should seek methods to close the reality gap between developers and users of AI solutions, but also define new job profiles, which are needed to develop, implement, integrate, and maintain AI-based solutions. Methods to identify, clarify, and communicate the currently uncertain path from data to profit would substantially favour the adoption of AI by industry same as the clarification of the starting points for new AI adopters. Innovation leads to the development of new technologies that involve novel manufacturing concepts not covered by existing rules, normative standards, and industry practices. As such it occurs that industry standards and requirements will be required to be met without hampering the exploitation of the technology. Equally important will be to address gaps related to IPR and civil liability for AI-enabled produced parts, the provision of education services, the identification of protocols for technology qualification and certification. To conclude, despite the achievements nowadays, there is yet research and implementation work to be done to fully realize the potential of AI in the EU industry and address open challenges, such as the need for human-centric, democratic, and resilient manufacturing systems, complying with the requirements for sustainability, and minimized environmental impact.

7 References

A.T.Kearney. (2017). Technology and innovation for the future of production: accelerating value creation. In World Economic Forum (Issue March, pp. 1–36). http://www3.weforum.org/docs/WEF_White_Paper_Technology_Innovation_Future_of_Production_2017.pdf

Abdar, M., Pourpanah, F., Hussain, S., Rezazadegan, D., Liu, L., Ghavamzadeh, M., Fieguth, P., Cao, X., Khosravi, A., Acharya, U. R., Makarenkov, V., & Nahavandi, S. (2021). A review of uncertainty quantification in deep learning: Techniques, applications and challenges. Information Fusion, 76, 243–297. https://doi.org/10.1016/j.inffus.2021.05.008

Aivaliotis, P., Arkouli, Z., Georgoulias, K., & Makris, S. (2021). Degradation curves integration in physics-based models: Towards the predictive maintenance of industrial robots. Robotics and Computer-Integrated Manufacturing, 71, 102177. https://doi.org/10.1016/j.rcim.2021.102177

Aivaliotis, P., Georgoulias, K., Arkouli, Z., & Makris, S. (2019). Methodology for enabling Digital Twin using advanced physics-based modelling in predictive maintenance. Procedia CIRP, 81, 417–422. https://doi.org/10.1016/j.procir.2019.03.072

Aivaliotis, P., Papalitsa, E., Michalos, G., & Makris, S. (2020). Identification of dynamic robot's parameters using physics-based simulation models for improving accuracy. Procedia CIRP, 96, 254–259. https://doi.org/10.1016/j.procir.2021.01.083

Aivaliotis, P., Zampetis, A., Michalos, G., & Makris, S. (2017). A Machine Learning Approach for Visual Recognition of Complex Parts in Robotic Manipulation. Procedia Manufacturing, 11, 423–430. https://doi.org/10.1016/j.promfg.2017.07.130

Aivaliotis, Panagiotis, Arkouli, Z., Georgoulias, K., & Makris, S. (2023). Methodology for enabling dynamic digital twins and virtual model evolution in industrial robotics - a predictive maintenance application. International Journal of Computer Integrated Manufacturing, 00(00), 1–19. https://doi.org/10.1080/0951192X.2022.2162591

Alexopoulos, K., Koukas, S., Boli, N., & Mourtzis, D. (2017). Resource planning for the installation of industrial product service systems. IFIP Advances in Information and Communication Technology, 514, 205–213. https://doi.org/10.1007/978-3-319-66926-7_24

Alexopoulos, K., Nikolakis, N., & Chryssolouris, G. (2020). Digital twin-driven supervised machine learning for the development of artificial intelligence applications in manufacturing. 33(5), 429–439. https://doi.org/10.1080/0951192X.2020.1747642

Alexopoulos, K., Sipsas, K., Xanthakis, E., Makris, S., & Mourtzis, D. (2018). An industrial Internet of things based platform for context-aware information services in manufacturing. International Journal of Computer Integrated Manufacturing, 31(11), 1111–1123. https://doi.org/10.1080/0951192X.2018.1500716

Alexopoulos, K., Weber, M., Trautner, T., Manns, M., Nikolakis, N., Weigold, M., & Engel, B. (2023). An industrial data-spaces framework for resilient manufacturing value chains. Procedia CIRP, 116, 299-304.

Andrianakos, G., Dimitropoulos, N., Michalos, G., & Makris, S. (2020). An approach for monitoring the execution of human based assembly operations using machine learning. Procedia CIRP, 86, 198–203. https://doi.org/10.1016/j.procir.2020.01.040

Andronas, D., Arkouli, Z., Zacharaki, N., Michalos, G., Sardelis, A., Papanikolopoulos, G., & Makris, S. (2022). On the perception and handling of deformable objects – A robotic cell for white goods industry. Robotics and Computer-Integrated Manufacturing, 77, 102358. https://doi.org/10.1016/j.rcim.2022.102358

Andronas, Dionisis, Kampourakis, E., Bakopoulou, K., Gkournelos, C., Angelakis, P., & Makris, S. (2021). Model-Based Robot Control for Human-Robot Flexible Material Co-Manipulation. IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 2021-September. https://doi.org/10.1109/ETFA45728.2021.9613235

Arkouli, Z., Aivaliotis, P., & Makris, S. (2020). Towards accurate robot modelling of flexible robotic manipulators. Procedia CIRP, 97, 497–501. https://doi.org/10.1016/j.procir.2020.07.009

Arkouli, Z., Kokotinis, G., Michalos, G., Dimitropoulos, N., & Makris, S. (2021). AI-enhanced cooperating robots for reconfigurable manufacturing of large parts. IFAC-PapersOnLine, 54(1), 617–622. https://doi.org/10.1016/J.IFACOL.2021.08.072

Arkouli, Zoi, Michalos, G., & Makris, S. (2022). On the Selection of Ergonomics Evaluation Methods for Human Centric Manufacturing Tasks. Procedia CIRP, 107, 89–94. https://doi.org/10.1016/j.procir.2022.04.015

Bampoula, X., Siaterlis, G., Nikolakis, N., & Alexopoulos, K. (2021). A deep learning model for predictive maintenance in cyber-physical production systems using lstm autoencoders. Sensors, 21(3), 972.

Bastani, O., Pu, Y., & Solar-Lezama, A. (2018). Verifiable Reinforcement Learning via Policy Extraction. Advances in Neural Information Processing Systems, 2018-December, 2494–2504. https://doi.org/10.48550/arxiv.1805.08328

Belkadi, F., Boli, N., Usatorre, L., Maleki, E., Alexopoulos, K., Bernard, A., & Mourtzis, D. (2017). A knowledge-based collaborative platform for PSS design and production.

Bingqian Yang , Zeng Yuanyi, Yang Hai, Penalva Oscoz, Mariluz, Ortiz, Mikel Frans Coenen, & Anh Nguyen (2022), Spring Back Prediction Using Point Series and Deep Learning, PREPRINT. courtesy: TECNALIABorgo, S., Cesta, A., Orlandini, A., & Umbrico, A. (2016). A planning-based architecture for a reconfigurable manufacturing system. Proceedings International Conference on Automated Planning and Scheduling, ICAPS, 2016-Janua(Icaps), 358–366.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D. M., Wu, J., Winter, C., … Amodei, D. (2020). Language models are few-shot learners. Advances in Neural Information Processing Systems, 2020-Decem.

Bugatti, M., & Colosimo, B. M. (2022). Towards real-time in-situ monitoring of hot-spot defects in L-PBF: a new classification-based method for fast video-imaging data analysis. Journal of Intelligent Manufacturing, 33(1), 293–309.

Burkart, N., & Huber, M. F. (2021). A Survey on the Explainability of Supervised Machine Learning. Journal of Artificial Intelligence Research, 70, 245–317. https://doi.org/10.1613/JAIR.1.12228

Cerquitelli, T., Nikolakis, N., O'Mahony, N., Macii, E., Ippolito, M., & Makris, S. Predictive Maintenance in Smart Factories. Springer 2021. Information Fusion and Data Science Series. DOI: 10.1007/978-981-16-2940-2. ISBN: 978-981-16-2939-6, pp. 234

Cerquitelli, T., Pagliari, D. J., Calimera, A., Bottaccioli, L., Patti, E., Acquaviva, A., & Poncino, M. (2021). Manufacturing as a Data-Driven Practice: Methodologies, Technologies, and Tools. Proceedings of the IEEE, 109(4), 399–422. https://doi.org/10.1109/JPROC.2021.3056006

Cesta, A, Cortellessa, G., Fratini, S., & Oddi, A. (2008). Looking for MrSPOCK: Issues in Deploying a Space Application. SPARK-08. ICAPS Workshop on Scheduling and Planning Applications, Sydney, Australia. https://www.researchgate.net/publication/268414142

Cesta, Amedeo, Cortellessa, G., Fratini, S., Oddi, A., & Policella, N. (2007). An innovative product for space Mission Planning an a posteriori evaluation. ICAPS 2007, 17th International Conference on Automated Planning and Scheduling, 57–64. www.aaai.org

Cesta, Amedeo, Fratini, S., Orlandini, A., Finzi, A., & Tronci, E. (2011). Flexible Plan Verification: Feasibility Results. Fundamenta Informaticae, 107(2–3), 111–137. https://doi.org/10.3233/FI-2011-397

Cesta, Amedeo, Orlandini, A., Bernardi, G., & Umbrico, A. (2016). Towards a planning-based framework for symbiotic human-robot collaboration. IEEE International Conference on Emerging Technologies and Factory Automation, ETFA, 2016-November. https://doi.org/10.1109/ETFA.2016.7733585

Chryssolouris, G. (2006). Manufacturing Systems: Theory and Practice. In Springer. Springer-Verlag. https://doi.org/10.1007/0-387-28431-1

Chryssolouris, G., Alexopoulos, K., & Arkouli, Z. (2023). A Perspective on Artificial Intelligence in Manufacturing (Vol. 436). Springer Nature.

Chryssolouris, George, Alexopoulos, K., & Arkouli, Z. (2023). Artificial Intelligence in Manufacturing Equipment, Automation, and Robots. 41–78. https://doi.org/10.1007/978-3-031-21828-6_3

Chryssolouris, George, Dicke, K., & Lee, M. (1994). An approach to real-time flexible scheduling. International Journal of Flexible Manufacturing Systems, 6(3), 235–253. https://doi.org/10.1007/BF01328813

Cialdea, M. M., Orlandini, A., & Umbrico, A. (2016). Planning and execution with flexible timelines: a formal account. Acta Informatica, 53(6–8), 649–680. https://doi.org/10.1007/s00236-015-0252-z

Colosimo, B. M., & Grasso, M. (2018). Spatially weighted PCA for monitoring video image data with application to additive manufacturing. Journal of Quality Technology, 50(4), 391–417. https://doi.org/10.1080/00224065.2018.1507563

Dan, Y., Zhao, Y., Li, X., Li, S., Hu, M., & Hu, J. (2020). Generative adversarial networks (GAN) based efficient sampling of chemical composition space for inverse design of inorganic materials. Npj Computational Materials, 6(1), 1–7. https://doi.org/10.1038/s41524-020-00352-0

Dimitropoulos, N., Michalos, G., & Makris, S. (2020). An outlook on future hybrid assembly systems - The Sherlock approach. Procedia CIRP, 97, 441–446. https://doi.org/10.1016/j.procir.2020.08.004

Dimitropoulos, N., Togias, T., Zacharaki, N., Michalos, G., & Makris, S. (2021). Seamless human–robot collaborative assembly using artificial intelligence and wearable devices. Applied Sciences (Switzerland), 11(12). https://doi.org/10.3390/app11125699

Ding, K., Jiang, P. Y., & Zhang, X. (2013). A framework for implementing social manufacturing system based on customized community space configuration and organization. Advanced Materials Research, 712–715, 3191–3194. https://doi.org/10.4028/www.scientific.net/AMR.712-715.3191

Duray, R. (2002). Mass customization origins: Mass or custom manufacturing? International Journal of Operations and Production Management, 22(3), 314–328. https://doi.org/10.1108/01443570210417614

Evangelou, G., Dimitropoulos, N., Michalos, G., & Makris, S. (2020). An approach for task and action planning in Human-Robot Collaborative cells using AI. Procedia CIRP, 97, 476–481. https://doi.org/10.1016/j.procir.2020.08.006

Foderaro, E., Cesta, A., Umbrico, A., & Orlandini, A. (2021). Simplifying the A.I. planning modeling for human-robot collaboration. 2021 30th IEEE International Conference on Robot and Human Interactive Communication, RO-MAN 2021, 1011–1016. https://doi.org/10.1109/RO-MAN50785.2021.9515431

Foteinopoulos, P., Papacharalampopoulos, A., & Stavropoulos, P. (2018). On thermal modeling of Additive Manufacturing processes. CIRP Journal of Manufacturing Science and Technology, 20, 66–83. https://doi.org/10.1016/J.CIRPJ.2017.09.007

Freitag, M., & Hildebrandt, T. (2016). Automatic design of scheduling rules for complex manufacturing systems by multi-objective simulation-based optimization. CIRP Annals, 65(1), 433–436. https://doi.org/10.1016/J.CIRP.2016.04.066

Friedman, J. H. (2001). Greedy function approximation: A gradient boosting machine. Annals of Statistics, 29(5), 1189–1232. https://doi.org/10.1214/aos/1013203451

García-Díaz, A., Panadeiro, V., Lodeiro, B., Rodríguez-Araújo, J., Stavridis, J., Papacharalampopoulos, A., & Stavropoulos, P. (2018). OpenLMD, an open source middleware and toolkit for laser-based additive manufacturing of large metal parts. Robotics and Computer-Integrated Manufacturing, 53, 153–161. https://doi.org/10.1016/J.RCIM.2018.04.006

Garghetti, F., Grasso, M., Pacella, M., Fogliazza, G., Colosimo, B.M. (2022), Multi-stream big data mining for industry 4.0 in machining: novel application of a Gated Recurrent Unit Network, 16th CIRP Conference on Intelligent Computation in Manufacturing Engineering, CIRP ICME '22, Italy

Ghallab, M., Ghallab, M., & Laruelle, H. (1994). Representation and Control in Ixtet, a Temporal Planner. IN AIPS, 61--67. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.488.4150

Gil Del Val, A., Penalva, M., Veiga, F., & Iriondo, E. (2022), An approach from the manufacturing chain and visual analytics for quality monitoring of blind fasteners installation, PREPRINT. courtesy: TECNALIA

Goodfellow, I., Pouget-Abadie, J., Mirza, M.B. Xu, D. Warde-Farley, S. Ozair, A. Courville, & Bengio, Y. (2014), Generative adversarial nets, Advances in neural information processing systems 27

Giordano, D., Pastor, E., Giobergia, F., Cerquitelli, T., Baralis, E., Mellia, M., Neri, A., & Tricarico, D. (2021). Dissecting a data-driven prognostic pipeline: A powertrain use case. Expert Systems with Applications, 180(March 2020). https://doi.org/10.1016/j.eswa.2021.115109

González-Val, C., & Muiños-Landin, S. (2018). Generative design for Social Manufacturing. https://www.formfutura.com/

Gosselin, F., Kchir, S., Acher, G., Keith, F., Lebec, O., Louison, C., Luvison, B., De Chamisso, F. M., Meden, B., Morelli, M., Perochon, B., Rabarisoa, J., Vienne, C., & Ameyugo, G. (2022). Robot Companion, an intelligent interactive robot coworker for the Industry 5.0. IEEE International Conference on Intelligent Robots and Systems, 2022-October, 8918–8925. https://doi.org/10.1109/IROS47612.2022.9982004

Grappiolo, C., Pruim, R., Faeth, M., & de Heer, P. (2021). ViTroVo: in vitro assembly search for in vivo adaptive operator guidance. The International Journal of Advanced Manufacturing Technology 2021, 1–21. https://doi.org/10.1007/S00170-021-07824-7

Jonsson, A. K., Morris, P. H., Muscettola, N., Rajan, K., & Smith, B. (2000). Planning in Interplanetary Space: Theory and practice. AIPS, 177–86. www.aaai.org

Kim, Y., Lee, H., & Kim, C. O. (2023). A variational autoencoder for a semiconductor fault detection model robust to process drift due to incomplete maintenance. Journal of Intelligent Manufacturing, 34(2), 529–540. https://doi.org/10.1007/s10845-021-01810-2

Kingma, D. P., & Welling, M. (2019). An introduction to variational autoencoders. Foundations and Trends® in Machine Learning, 12(4), 307-392. Uzunova H, Wilms M, Forkert ND, Handels H, Ehrhardt J. A systematic comparison of generative models for medical images. Int J Comput Assist Radiol Surg. 2022 Jul;17(7):1213-1224. doi: 10.1007/s11548-022-02567-6

Kokotinis, G., Michalos, G., Arkouli, Z., & Makris, S. (2023). On the quantification of human-robot collaboration quality. International Journal of Computer Integrated Manufacturing. https://doi.org/10.1080/0951192X.2023.2189304

Kousi, N., Dimosthenopoulos, D., Matthaiakis, A. S., Michalos, G., & Makris, S. (2020). AI based combined scheduling and motion planning in flexible robotic assembly lines. Procedia CIRP, 86, 74–79. https://doi.org/10.1016/j.procir.2020.01.041

Kousi, N., Gkournelos, C., Aivaliotis, S., Giannoulis, C., Michalos, G., & Makris, S. (2019). Digital twin for adaptation of robots' behavior in flexible robotic assembly lines. Procedia Manufacturing, 28, 121–126. https://doi.org/10.1016/j.promfg.2018.12.020

Kousi, N., Gkournelos, C., Aivaliotis, S., Lotsaris, K., Bavelos, A. C., Baris, P., Michalos, G., & Makris, S. (2021). Digital Twin for Designing and Reconfiguring Human–Robot Collaborative Assembly Lines. Applied Sciences 2021, Vol. 11, Page 4620, 11(10), 4620. https://doi.org/10.3390/APP11104620

Lemai, S., & Ingrand, F. (2004). Interleaving temporal planning and execution in robotics domains. Proceedings of the National Conference on Artificial Intelligence, 617–622. www.aaai.org

Lipton, Z. C. (2018). The mythos of model interpretability. Communications of the ACM, 61(10), 35–43. https://doi.org/10.1145/3233231

Lopez-Garcia, P., Barrenetxea, X., García-Arrieta, S., Sedano, I., Palenzuela, L., & Usatorre, L. (2022). Compounding process optimization for recycled materials using machine learning algorithms. Procedia CIRP, 105, 237–242. https://doi.org/10.1016/j.procir.2022.02.039

Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 2017-Decem, 4766–4775. https://doi.org/10.5555/3295222

Makris, S. (2021). Cooperating Robots for Flexible Manufacturing. http://link.springer.com/10.1007/978-3-030-51591-1

Makris, S., Kampourakis, E., & Andronas, D. (2022). On deformable object handling: Model-based motion planning for human-robot co-manipulation. CIRP Annals. https://doi.org/10.1016/J.CIRP.2022.04.048

Makris, S., Tsarouchi, P., Surdilovic, D., & Krüger, J. (2014). Intuitive dual arm robot programming for assembly operations. CIRP Annals, 63(1), 13–16. https://doi.org/10.1016/J.CIRP.2014.03.017

Michalos, G., Karagiannis, P., Dimitropoulos, N., Andronas, D., & Makris, S. (2022). Human robot collaboration in industrial environments. The 21st century industrial robot: when tools become collaborators, 17-39.

Meyers, B., Van Noten, J., Lietaert, P., Tielemans, B., Hristov, H., Maes, D., & Gadeyne, K. (2022). Knowledge Graphs in Digital Twins for Manufacturing-Lessons Learned from an Industrial Case at Atlas Copco Airpower. IFAC-PapersOnLine, 55(10), 13-18.

Michalos, G, Makris, S., & Mourtzis, D. (2012). An intelligent search algorithm-based method to derive assembly line design alternatives. International Journal of Computer Integrated Manufacturing, 25(3), 211–229. https://doi.org/10.1080/0951192X.2011.627949

Michalos, George, Karvouniari, A., Dimitropoulos, N., Togias, T., & Makris, S. (2018). Workplace analysis and design using virtual reality techniques. CIRP Annals, 67(1), 141–144. https://doi.org/10.1016/j.cirp.2018.04.120

Michalos, George, Kousi, N., Karagiannis, P., Gkournelos, C., Dimoulas, K., Koukas, S., Mparis, K., Papavasileiou, A., & Makris, S. (2018). Seamless human robot collaborative assembly – An automotive case study. Mechatronics, 55, 194–211. https://doi.org/10.1016/j.mechatronics.2018.08.006

Michalos, George, Makris, S., Spiliotopoulos, J., Misios, I., Tsarouchi, P., & Chryssolouris, G. (2014). ROBO-PARTNER: Seamless human-robot cooperation for intelligent, flexible and safe operations in the assembly factories of the future. Procedia CIRP, 23(C), 71–76. https://doi.org/10.1016/j.procir.2014.10.079

Mohajeri, B., Advisor, T., Nyberg, T., & Hämäläinen, M. (2015). Paradigm Shift from Current Manufacturing to Social Manufacturing Title of thesis: Paradigm Shift from Current Manufacturing to Social Manufacturing.

Morris, P., & Muscettola, N. (2005). Temporal dynamic controllability revisited. Proceedings of the National Conference on Artificial Intelligence, 3, 1193–1198.

Orlandini, A., Bernardi, G., Cesta, A., & Finzi, A. (2014). Planning meets verification and validation in a knowledge engineering environment. Intelligenza Artificiale, 8(1), 87–100. https://doi.org/10.3233/IA-140063

Orlandini, A., Suriano, M., Cesta, A., & Finzi, A. (2013). Controller synthesis for safety critical planning. Proceedings - International Conference on Tools with Artificial Intelligence, ICTAI, 306–313. https://doi.org/10.1109/ICTAI.2013.54

Pandremenos, J., & Chryssolouris, G. (2011). A neural network approach for the development of modular product architectures. International Journal of Computer Integrated Manufacturing, 24(10), 879–887. https://doi.org/10.1080/0951192X.2011.602361

Papacharalampopoulos, A., Giannoulis, C., Stavropoulos, P., & Mourtzis, D. (2020). A Digital Twin for Automated Root-Cause Search of Production Alarms Based on KPIs Aggregated from IoT. Applied Sciences 2020, Vol. 10, Page 2377, 10(7), 2377. https://doi.org/10.3390/APP10072377

Papacharalampopoulos, A., Michail, C. K., & Stavropoulos, P. (2021). Manufacturing resilience and agility through processes digital twin: design and testing applied in the LPBF case. Procedia CIRP, 103, 164–169. https://doi.org/10.1016/J.PROCIR.2021.10.026

Papacharalampopoulos, A., Stavropoulos, P., & Stavridis, J. (2018). Adaptive Control of Thermal Processes: Laser Welding and Additive Manufacturing Paradigms. Procedia CIRP, 67, 233–237. https://doi.org/10.1016/J.PROCIR.2017.12.205

Papacharalampopoulos, A., Tzimanis, K., & Stavropoulos, P. (2022). A decision support tool for dynamic LCA: The FDM paradigm. Procedia CIRP, 112, 543–548. https://doi.org/10.1016/j.procir.2022.09.097

Pellegrinelli, S., Orlandini, A., Pedrocchi, N., Umbrico, A., & Tolio, T. (2017). Motion planning and scheduling for human and industrial-robot collaboration. CIRP Annals, 66(1), 1–4. https://doi.org/10.1016/J.CIRP.2017.04.095

Rentzos, L., Vourtsis, C., Mavrikios, D., & Chryssolouris, G. (2014). Using VR for Complex Product Design. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 8526 LNCS(PART 2), 455–464. https://doi.org/10.1007/978-3-319-07464-1_42

Ribeiro, M. T., Singh, S., & Guestrin, C. (2016). “Why should i trust you?” Explaining the predictions of any classifier. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 13-17-August-2016, 1135–1144. https://doi.org/10.1145/2939672.2939778

Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature Machine Intelligence 2019 1:5, 1(5), 206–215. https://doi.org/10.1038/s42256-019-0048-x

Sardelis, A., Zacharaki, N. C., Arkouli, Z., Andronas, D., Michalos, G., Makris, S., & Papanikolopoulos, G. (2020). 2-Stage vision system for robotic handling of flexible objects. Procedia CIRP, 97, 491–496. https://doi.org/10.1016/j.procir.2020.07.008

Schaaf, N., Huber, M., & Maucher, J. (2019). Enhancing decision tree based interpretation of deep neural networks through L1-orthogonal regularization. Proceedings - 18th IEEE International Conference on Machine Learning and Applications, ICMLA 2019, 42–49. https://doi.org/10.1109/ICMLA.2019.00016

Stavropoulos, P., Papacharalampopoulos, A., Vasiliadis, E., & Chryssolouris, G. (2016). Tool wear predictability estimation in milling based on multi-sensorial data. The International Journal of Advanced Manufacturing Technology 2015 82:1, 82(1), 509–521. https://doi.org/10.1007/S00170-015-7317-6

Stavropoulos, Panagiotis, Papacharalampopoulos, A., & Athanasopoulou, L. (2020). A molecular dynamics based digital twin for ultrafast laser material removal processes. International Journal of Advanced Manufacturing Technology, 108(1–2), 413–426. https://doi.org/10.1007/s00170-020-05387-7

Stavropoulos, Panagiotis, Papacharalampopoulos, A., Michail, C. K., & Chryssolouris, G. (2021). Robust Additive Manufacturing Performance through a Control Oriented Digital Twin. Metals 2021, Vol. 11, Page 708, 11(5), 708. https://doi.org/10.3390/MET11050708

Stavropoulos, Panagiotis, Papacharalampopoulos, A., & Sampatakakis, K. (2020). A CPS platform oriented for Quality Assessment in welding. MATEC Web of Conferences, 318, 01030. https://doi.org/10.1051/MATECCONF/202031801030

Stavropoulos, Panagiotis, Papacharalampopoulos, A., Stavridis, J., & Sampatakakis, K. (2020). A three-stage quality diagnosis platform for laser-based manufacturing processes. International Journal of Advanced Manufacturing Technology, 110(11–12), 2991–3003. https://doi.org/10.1007/S00170-020-05981-9/FIGURES/16

Tsarouchi, P., Michalos, G., Makris, S., Athanasatos, T., Dimoulas, K., & Chryssolouris, G. (2017). On a human–robot workplace design and task allocation system. International Journal of Computer Integrated Manufacturing, 30(12), 1272–1279. https://doi.org/10.1080/0951192X.2017.1307524

Tsarouchi, P., Spiliotopoulos, J., Michalos, G., Koukas, S., Athanasatos, A., Makris, S., & Chryssolouris, G. (2016). A Decision Making Framework for Human Robot Collaborative Workplace Generation. Procedia CIRP, 44, 228–232. https://doi.org/10.1016/j.procir.2016.02.103

Umbrico, A., Cesta, A., Cialdea Mayer, M., & Orlandini, A. (2017). PLATINUm: A new framework for planning and acting. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 10640 LNAI, 498–512. https://doi.org/10.1007/978-3-319-70169-1_37/FIGURES/1

Umbrico, A., Cesta, A., Mayer, M. C., & Orlandini, A. (2018). Integrating resource management and timeline-based planning. Proceedings International Conference on Automated Planning and Scheduling, ICAPS, 2018-June(Icaps), 264–272.

Umbrico, A., Orlandini, A., & Cesta, A. (2020). An Ontology for Human-Robot Collaboration. Procedia CIRP, 93, 1097–1102. https://doi.org/10.1016/J.PROCIR.2020.04.045

Vidal, T., & Fargier, H. (1999). Handling contingency in temporal constraint networks: From consistency to controllabilities. Journal of Experimental and Theoretical Artificial Intelligence, 11(1), 23–45. https://doi.org/10.1080/095281399146607

Viola, C. La, Orlandini, A., Umbrico, A., & Cesta, A. (2020). ROS-TiPlEx: A collaborative design tool for Timeline-based Planning & Scheduling applications with ROS.

Vonrueden, L., Mayer, S., Beckh, K., Georgiev, B., Giesselbach, S., Heese, R., Kirsch, B., Walczak, M., Pfrommer, J., Pick, A., Ramamurthy, R., Garcke, J., Bauckhage, C., & Schuecker, J. (2021). Informed Machine Learning - A Taxonomy and Survey of Integrating Prior Knowledge into Learning Systems. IEEE Transactions on Knowledge and Data Engineering. https://doi.org/10.1109/TKDE.2021.3079836

