knowlEdge Project – Concept, Methodology and Innovations for Artificial Intelligence in Industry 4.0

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***Abstract*—AI is one of the biggest megatrends towards the 4th industrial revolution. Although these technologies promise business sustainability as well as product and process quality, it seems that the ever-changing market demands, the complexity of technologies and fair concerns about privacy, impede broad application and reuse of Artificial Intelligence (AI) models across the industry. To break the entry barriers for these technologies and unleash its full potential, the *knowlEdge* project will develop a new generation of AI methods, systems, and data management infrastructure. Subsequently, as part of the *knowlEdge* project we propose several major innovations in the areas of data management, data analytics and knowledge management including (i) a set of AI services that allows the usage of edge deployments as computational and live data infrastructure as well as a continuous learning execution pipeline on the edge, (ii) a digital twin of the shop-floor able to test AI models, (iii) a data management framework deployed along the edge-to-cloud continuum ensuring data quality, privacy and confidentiality, (iv) Human-AI Collaboration and Domain Knowledge Fusion tools for domain experts to inject their experience into the system, (v) a set of standardisation mechanisms for the exchange of trained AI models from one context to another, and (vi) a knowledge marketplace platform to distribute and interchange trained AI models. In this paper, we present a short overview of the EU Project *knowlEdge – Towards Artificial Intelligence powered manufacturing services, processes, and products in an edge-to-cloud-knowledge continuum for humans* [*in-the-loop*], which is funded by the Horizon 2020 (H2020) Framework Programme of the European Commission under Grant Agreement 957331. Our overview includes a description of the project's main concept and methodology as well as the envisioned innovations.**

***Index Terms*—Artificial Intelligence, Machine Learning, Data Analytics, Industry 4.0, Smart Process Manufacturing, Human-AI Collaboration**

I. Introduction

Over the years, industries around the world have been investing resources to improve efficiency, effectiveness and responsiveness of their manufacturing systems [2]–[7]. However challenges such as unprecedented instability that threatens the responsiveness of formal planning systems, and continuous improvement of manual engineering techniques have highlighted the inability of the existing methods. In order to

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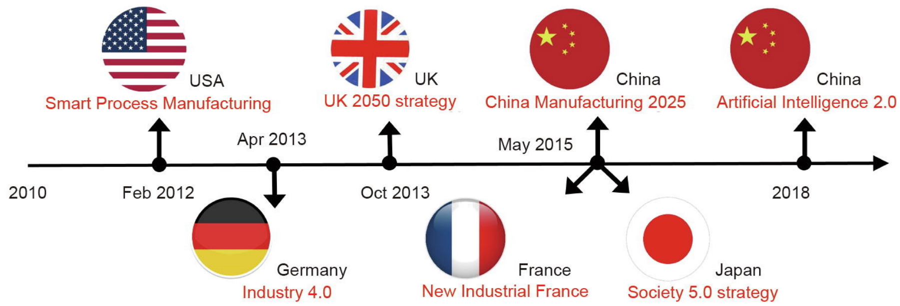

Fig. 1. Overview of different governmental programs. Image taken from [1].

remain competitive, manufacturers seek new ways that ensure dynamic response to changes in technology, materials, but also to the customer preferences [8]. In this regard, techniques and systems that generate knowledge from available data while being replicable and dynamic, are imminent and much needed.

The demand in the global market for smart and agile manufacturing solutions [2], [9] has been rising based on the emerging need for making manufacturing activities more profitable, carbon neutral and circular. The global market for smart manufacturing is forecasted to reach a value of USD 548.14 billion by the year 2024, elevating from a total worth of USD 159.05 billion in the year 2015 [10].

In order to keep its leading position, the European manufacturing sector needs to make its activities and processes more sustainable, highly efficient, and transition to minimum tolerance of defects. These optimized activities need to be well aligned with rapidly changing customers requirements and market trends [11], [12]. As shown in Figure 1, Artificial Intelligence (AI) as part of the new industrial revolution is currently trending across many national strategies [1] as a promising solution for addressing dynamic industrial needs. According to a recent study [13], manufacturing based on AI can generate an annual USD 3.8 trillion in GVA by 2035. AI has contributed towards remarkable progress in several fields, including computer vision [14], data analytics [15] and machine automation [16]. Although AI is already playing an important role in enabling EU industries to achieve disruptive transformations, improving process management and increasing efficiency (e.g. through intelligent utilization of materials and energy consumption), the potential of AI is by far not yet fully exploited [17].

In the near future the combination of AI techniques with other technologies such as big data analytics, robotics, simulation technologies, industrial Internet of Things (IoT), cloud computing, will usher in the 4th industrial revolution [18], [19]. Some of the benefits that can still be achieved through effective utilization of AI techniques include dynamic response to changes in market demands, getting products to the market in shorter time, more efficient supply chain, more dynamic processes, etc [17]. Following [20], AI technologies can enable smart machines to extend human capabilities (sensing, acting, learning), thus allowing people to achieve more. Still, AI - human communication is in its infancy, since humans are usually not able to transfer their knowledge into the system, neither use it properly. Hence, the challenge is to design, justify and deploy new AI -based technologies and methods for supporting the new industrial revolution.

AI offers huge advantages over traditional automation. According to Accenture [21], AI could double the annual economic growth rates by the year 2035 and create new relationships between people and machines, keeping people in control. Efficient big data analytics and AI models generated for manufacturing IoT could

- improve the factory operations and production,
- reduce machine downtime,
- improve product quality,
- enhance supply chain efficiency,
- increase resource and energy efficiency,
- warrant safety and risk management,
- orchestrate the pathway to a carbon-neutral economy, and
- improve the customer experience.

Furthermore, an increase in responsiveness within supply networks is envisioned if Explainable AI (XAI) simulations, visualizations, notifications, etc., are provided to decision-makers [21]. The capability of AI techniques and technologies is further enhanced when these are distributed in the computing continuum. For instance, cloud technologies provide the opportunity to scale rapidly with lower computing costs [22]. On the other hand, computation at the edge and on the fog drastically improves response time [23]. Moreover, AI with human-in-the-loop allows further increase in flexibility, agility and competitiveness. This also support skill development and increased competitiveness. The use of transparent and XAI solutions allows humans to be trained and to develop their individual skills through knowledge capturing mechanisms. The human-AI collaboration is expected to play an essential role towards knowledge generation and decision making.

To do so, AI models will have to produce human-centered explanations. The *knowlEdge* project commits to the challenge of creating models and techniques that both accurate and provide good trustworthy explanation that will satisfies customers' needs. From a business, ethical and regulatory point of view, explainability is essential for users to trust and manage AI results appropriately [24]. The explainability depends to a large extent on what is to be explained, how the explanation is made and who will receive it. Therefore,

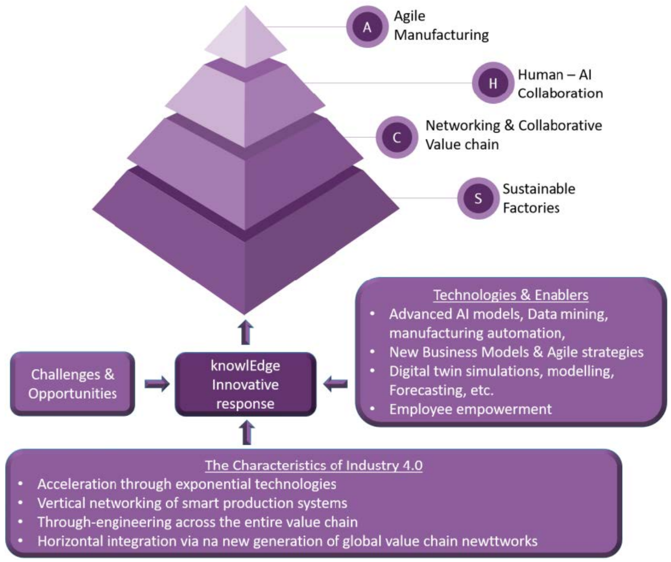

Fig. 2. *knowlEdge* Project Innovation Response

it is important to think about why and when explanations are useful. To achieve this, it will be necessary to analyze the concept of explainability as well as its degree, for each case study. However, as discussed in [25], providing interpretable algorithms could in general allow us

- to ensure there is a testable and auditable way to defend algorithmic decisions as being fair and ethical, which leads to building trust,
- to enhance control providing greater visibility over unknown vulnerabilities and flaws, and helping to identify and correct errors, and
- to provide explanations in order to easily improve models.

Undoubtedly, communicating complex computational processes to human will represent a challenge for designing XAI.

In this paper, we present a short overview of the EU Project *knowlEdge – Towards Artificial Intelligence powered manufacturing services, processes, and products in an edge-to-cloud-knowledge continuum for humans* [*in-the-loop*], which is funded by the H2020 Framework Programme of the European Commission under Grant Agreement 957331 and conducted from January 2021 until December 2023 with a consortium comprising 12 partners from 7 EU countries and 3 manufacturing domains (milk-, plastic-car-parts-, and gear-machines-industries).

The major aim of the *knowlEdge* Project is to develop a new generation of AI models (semi-automated knowledge discovery) and data management tools, and combine them with other technologies, tools and services (digital twin, decision support systems, etc.), in order to support humans to make decisions, collaborate better with AI systems, and fuse (human-AI) knowledge. The project's main aim is to boost industries towards agile and flexible strategies, able to respond to the fast-changing customers' needs, and in the same time to optimize their processes and quality control mechanisms. The innovation response of the *knowlEdge* Project is summarized in Figure 2.

The remainder of this paper is structured as follows. We will summarize the project's concept and methodology as well as the envisioned innovations in Section II, before we give a short overview about use cases and their objectives in Section III. The paper is concluded in Section IV.

II. Concept, Methodology and Innovations

"Agility in manufacturing is the ability to produce a broad range of low cost, high quality products with short lead times in varying lot sizes and built to individual customer specifications" [2]. *"Academics and practitioners have long acknowledged the importance of agile manufacturing in achieving sustainable competitiveness"* [2]. Agile manufacturing aims at helping companies to become more competitive and prosperous in challenging environments, where change is unanticipated and continuous [3]. In order to realize agile manufacturing, intelligent synthesis of technologies, tools and methods are essential for competing and satisfying customers' requirements, while big data analytics and AI are becoming a necessity to enhance the state of art in terms of product quality as well as the process quality, efficiency and agility.

In the modern manufacturing domain, there is a continuous and exponential growth of data coming from processes, machines, control systems, sensors and other IoT devices. In 2025, the volume of useful data is expected to exceed 16 zettabytes (16 Trillion GB) [26]. The development of advanced AI solutions capable of extracting valuable knowledge from heterogeneous data sources is therefore of paramount importance. However, knowledge extraction from big data firstly requires advanced techniques that allow to capture or harvest data from different sources in the domain, and secondly the expertise of deploying data analytic services to apply intelligence at different levels in the compute continuum; while optimizing the functional and non-functional parameters. Realizing advanced AI capabilities thus is not easily done due to the difficulty of integrating distributed data extraction and AI-based analytic capabilities into different types of industrial environments. There is therefore an urgent necessity to develop automated AI centric software solutions capable of making an efficient use of data and providing insight, knowledge or decision support at different levels of the compute continuum. In addition, gained process knowledge and solutions to specific problems are rarely or not at all shared between different entities of the same domain, although scenarios and equipment might be identical. Consequently the potential of related business models is lost.

The *knowlEdge* project will converge methods and techniques from multiple areas, including AI, distributed data analytics, embedded computing, IoT, Cyber-Physical Systems (CPS), software engineering, edge and Cloud technologies into a unified software architecture, where particularly the combined integration of IoT and data science functionalities is challenge [27] that has to be adressed. The outcomes of the project will not only enable the automated extraction and utilization of data coming from multiple and geographically dispersed sources, it will also provide a way of reusing and sharing AI models in an (semi-) automated way, in particular targeting companies that will be able not only to perform the execution of the models but also the training themselves. While doing so the *knowlEdge* project aims to deliver major innovations in different domains, as described in the remainder of this section.

A. Knowledge Discovery and Management Domain

From the knowledge discovery and management domain, the *knowlEdge* project will (semi-)automatically extract inherent and reusable knowledge from multiple heterogeneous big data sources by using state-of-the-art data mining and machine learning techniques such as semantic signal processing, feature analysis and clustering. This representative information is made accessible via efficient databases and utilized in subsequent AI processes and final data modeling stages. In order to allow for a semantic enrichment of this automatically extracted information, an interface for domain and process experts is established within the scope of the project. Via this interface, the *knowlEdge* platform will receive, in real-time, feedback from the users about the quality of the insights generated, and this feedback will be used in order to adjust or improve the discovery process.

B. Artificial Intelligence Domain

From an AI-centric perspective, the *knowlEdge* software architecture will develop smarter and frugal techniques for automated AI modeling, prioritizing the reuse and tuning of existing models whenever possible. Therefore, the *knowlEdge* project will allow for the development, training and validation of shareable/transferable AI models (e.g. via the combination of digital twins of physical world entities [28], [29] and transfer learning techniques [30], [31]). This approach will be abstract in order to mitigate the impact of the variable availability of big data and the data interoperability constraints and will produce computational artifacts and resources upon which the AI algorithms will be distributed in all layers of the continuum. The AI models will not only be created for behavioral analysis, but also to enable decision support and predictive simulation capabilities to provide reliable assessments. Models and algorithms are furthermore stored in a shared repository, which forms the basis for a common model marketplace that will include capabilities for the automatic selection and recommendation of models [32], [33].

C. Distributed and Parallel Computing Domain

Concerning the domain of distributed and parallel computing, the *knowlEdge* project will consider the most advanced software frameworks currently used to distribute computational intensive tasks (e.g., the COMP Superscalar (COMPS) development framework [34] developed at Barcelona Supercomputing Center (BSC) and used in the Marenostrum Supercomputer hosted by BSC, Spark [35]). These frameworks will be key to distribute and implement accurate knowledge management and machine learning techniques. The *knowlEdge* project will enhance this technology to (a) support AI-based model development through data gathering from the fog or across the compute continuum, and (b) efficiently distribute computations in according computing environments. This distribution will be guided not only based on performance criteria, but also considering the non-functional properties imposed by the system. The distribution mechanism will also enable the adaptation of AI models based on the newly acquired knowledge.

D. Digital and Multi-sided Platform Domain

From the digital and multi-sided platform domain, the *knowlEdge* software architecture will support the development of multi-sided platforms where stakeholders and process experts can retrieve, provide, inspect and manipulate knowledge via different interfaces. One central aspect for the retrieval and provisioning of knowledge is a common marketplace for AI models on top of an associated repository, which allows for a trade of pre-learned models between different stakeholders and thus facilitates for new business models. In addition, own and purchased models can be simulated and to some extend made understandable via digital twins. While it is often time consuming, costly and even risky to change the behavior of continuously running machines, digital twins solve this problem by testing different AI models, without changing the actual system.

E. Data Management and Governance Domain

From the data management and governance domain, the *knowlEdge* project will support the interaction between the physical and virtual (AI) world. In order to guarantee seamless interconnectivity and interoperability among data sources and AI models (e.g. enhanced by digital twins [28], [29]), standardized interconnections (e.g., FIWARE, EdgeXFoundry) will be employed. Through that, it is possible to manage, monitor and govern physical magnitudes, as well as actuating in the environment. Moreover, the governance mechanism in knowlEdge will guarantee the non-functional properties inherited from the cyber-physical interactions, i.e. data quality, real-time decision support, energy-efficiency, quality of communications and security. The data governance will focus on implemented mechanism for secure collection, storage, management and sharing of data. Proper data assurance will keep track of the quality of the data in the architecture based on predefined but configurable acceptable conditions.

F. Software Engineering and Cloud domain

From the software engineering and Cloud domain, the *knowlEdge* project will enable AI models or applications to adapt, scale and utilize resources in the fog environment by leveraging container technologies currently used on the Cloud, e.g., Kubernetes and Docker Swarm [36]. This unprecedented level of agility and flexibility will provide system developers with powerful tools to ensure that critical Service Level Agreements (SLAs) are respected, as events and data flows vary over time. Moreover, Cloud technology will be applied in knowlEdge to support data transport, parallel data processing and data persistency tasks. Finally, advanced and real-time monitoring will ensure overall system health can be assessed, as well as alerts raised if and when incidents are detected.

G. Human-centric Design and HCI Domain

From the human-centric design and Human-Computer Interaction (HCI) domain, the *knowlEdge* architecture will keep humans in the center, by developing the suitable interfaces (e.g. digital twin) that retrain and upskill the role of human in the AI solutions. The *knowlEdge* solutions maintain the vital role of humans as key decision making entity and as a vital collaborator in the future manufacturing environment where each actor (human, AI application) will learn from the other. knowlEdge will empower system operators through AI applications combining their capabilities in new ways to create value and extract knowledge, but also use the machine intelligence to enable humans make decisions.

H. Product Quality Domain

From the product quality domain, the *knowlEdge* approach represents a predictive quality management solution that is flexible, scalable and transparent. The distributed machine learning and knowledge management in knowlEdge proposes a concept for providing reliable information that can directly contribute towards product quality both in corrective and predictive scenarios. This should help operators and (intelligent) machines to find appropriate reactions to the downtrends, and suggest better process value trends for balancing out the current undesired situation.

To conclude, the envisioned concept and innovations of the *knowlEdge* project will lead to the development of a new generation of AI methods, systems and data management infrastructure. As shown in Figure 3, the *knowlEdge* project aims to (i) advance from traditional manufacturing processes to more agile processes which are able to timely adapt to changing market needs, (ii) enable quality inspection, prediction and control across all stages of production, (iii) provide dynamic process optimization in real-time, (iv) closely couple the collaboration between humans and AI in order to exchange knowledge and train employees and (v) enhance data and analysis intelligence within the compute continuum defined across edge, fog and cloud.

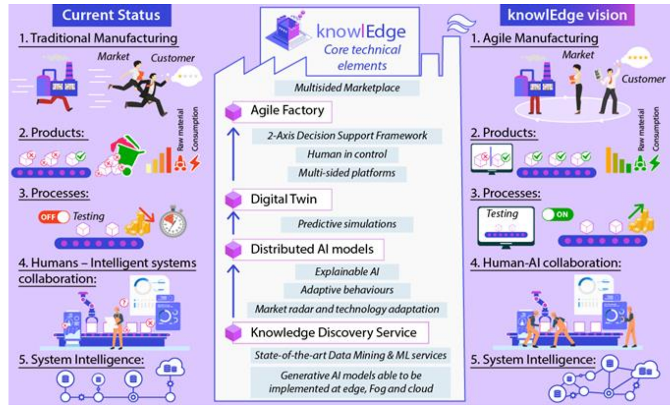

Fig. 3. Conceptual comparison between current practices and the envisioned future by means of the *knowlEdge* project.

III. Use Cases and Objectives

The *knowlEdge* project will be carried out on 3 pilot demonstrators (and 4 use cases) in order to verify the developed architecture. To ensure that the technologies and methodologies developed in the course of this project are applicable to a wide number of industrial scenarios, the 4 use cases have been selected from distinct manufacturing and process industries, namely food, plastic automotive components and gear-box machinery. These pilots present an evident need for AI-based adaptations to address industrial challenges related to product and process improvements, human engagements, making innovation easily understandable and useable by humans, as well as coupling innovation with security and knowledge. Despite the differences in the industrial environments and levels of automation, all pilot sites share common challenges related to data quality, lack of computational infrastructure to support big data analytics, lack of advanced Information Communications Technology (ICT) tools (e.g. AI services) in line with privacy and security legislation, and specific emphasis on non-functional properties of production processes e.g. energy efficiency, waste reduction etc. The solutions targeted in the *knowlEdge* project will be demonstrated and validated throughout physical pilot lines as well as through digital twin simulations. The objectives of the different use cases are described in the remainder of this section.

A. Continuous tracking of process and intelligent scheduling of production

The objective of this use case is to increase the number of information collected, about production and quality controls during and after the production, in order to create an optimal scheduled plan and adjust it in real time using the information from the field. The goals are to maximize the Overall Equipment Effectiveness (OEE), to improve the service level to the market and to standardize more precisely the final parameters of the products.

B. Production scheduling prediction to increase packaging and process efficiency

The objective of this use case is to extract information from different data streams (production data, warehouse data, product traceability, shop floor measurement, etc.), in order to predict the requested volume and to optimize internal warehouse management, to reduce raw material stock, to improve production flows, to reduce waste and, finally, to have a better coordination of production and logistics processes.

C. Production optimization for small batch

The objective of this use case is to put AI into practice by Implementing machine learning methods and technology for the purpose of increasing efficiency (lower scrap and unplanned downtime, increase OEE) and for improving product quality and competitiveness especially in the European market.

D. AI video analysis assembly supervisor

The objective of this use case is to ensure that all the steps (picking of components, mounting, screwing, …) described in the assembly work instructions will be executed carefully and sequentially by the shop floor workers and if not that an immediate alert is raised in order to prevent that an improperly assembled piece either goes to a next stage of assembly or (worse) to final customer destination. This monitoring should be performed by the analysis of the recorded video sequences of the assembly.

IV. Conclusions

In this paper, we have presented a short overview of the EU Project *knowlEdge – Towards AI powered manufacturing services, processes, and products in an edge-to-cloud-knowledge continuum for humans* [*in-the-loop*], which is funded by the H2020 Framework Programme of the European Commission under Grant Agreement 957331 and conducted from January 2021 until December 2023 with a consortium comprising 12 partners from 7 EU countries and 3 manufacturing domains (milk-, plastic-car-parts-, and gear-machines- industries). We have outlined the major aim of this project, which is to develop a new generation of AI models and data management tools, and combine them with other technologies, tools and services. In this way, the *knowlEdge* project aims to boost industries towards agile and flexible strategies, is able to respond to fast-changing customer needs, and at the same time optimizes their processes and quality control mechanisms.

With AI being one of the biggest megatrends towards the 4th industrial revolution, we believe that the innovations outlined above will lead to a new generation of AI-based manufacturing services and that the *knowlEdge* project will innovate the way how industrial solutions will be developed and applied in the future.

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