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[D1.1] AI & BD TECHNOLOGIES STATE-OF-THE-ART REVIEW

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Detailed notes on changes made based on PO's comments:

PAGE	CHANGES MADE
6	exec. summary, added explanation of original/DoA cube (and the original cube figure) as starting point and its evolution through D11 to D1.3
8	objectives, added extra explanation of deliverables.
12	state of the art, added explanation at start of Section
12 - 15	moved technology glossary from D1.3 to first section of section 5.
29	added explanation at beginning regarding international vs EU refs
34 - 36	new section 5.5 which evaluated international vs EU state of the art

37, 38	added extra explanations/interpretations of international vs European
39 - 40	Added maturity levels based on TRL Levels of EU projects
57	annex of detailed sector lit. review: added extra explanation at beginning.

Quality check review

Reviewer (s)	**Main changes**
Ron Weerdmeester	Place detailed literature review as annex and move most of section 6.1 to section 5.3. Remove section 5.4. Correct some details of the project literature search.
Taira Colah	Document editing and overall consistency check
Taira Colah	Corrected subtitle numbering. Removed highlight from text.

Table of contents

List of abbreviations and definitions

Please complete, in alphabetic order, with the abbreviations used in the document

Abbreviation	Definition
AI	Artificial Intelligence
ANN	Artificial Neural Networks
BD	Big Data
CPS	Cyber-Physical Systems
DoA	Description of Action
EC	European Commission
H2020	Horizon 2020
ML	Machine Learning
SPIRE	Sustainable Process Industry through Resource and Energy Efficiency

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1. EXECUTIVE SUMMARY

This report describes an overview of AI and BD technologies and their application degree in the SPIRE process industries.

The following consists of an overview of the AI and BD existing technologies which has been generated by means of literature review, examples of real experiences of participation in AI and BD projects, analysis of existing roadmaps at different levels (regional, national, and international), as well as focused intelligence activity for the identification of the most important research and innovation projects of H2020 and other EU framework programmes.

A comparison between roadmaps and running projects provides a preliminary picture of how technologies are under implementation and how projects already cover objectives set by roadmaps and strategic research agendas.

A first overall description of the technologies key features, maturity level and applicability will be outlined, providing an adequate starting point for the detailed mapping outlined in WP3 and the roadmap for process industry established in WP4.

The CUBE of Fig. 1 represents the original version (from the DoA), as initial starting point for the project and the deliverables of WP1. In D1.1 the Technologies dimension is reviewed by a detailed state of the art study, which is followed by a review in D1.2 of the Processes dimension (sector by sector), and the detailed findings of D1.1 and D1.2 and then consolidated and summarized in D1.3 to update the CUBE and produce the final dimension categories.

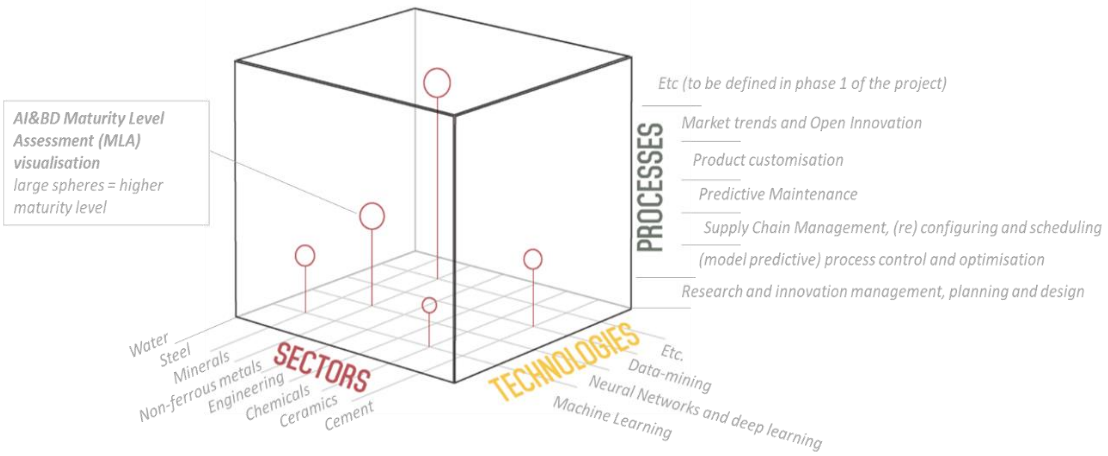

Figure 1. The original "CUBE" concept

Also, note that D1.1 represents a review of the "international" state of the art (as indicated in the DoA task description), as well as the specific EU situation in terms of a detailed list of publicly funded projects, country by country roadmaps, major industry players and practical examples of deployment and activity in the EU. Then, in D1.2 a closer focus is given to the EU process industries, sector by sector.

2. PROJECT INTRODUCTION

AI-CUBE seeks to enhance the understanding of different digital technologies related to artificial intelligence (AI) and big data (BD) applied in process industries for all the SPIRE industrial sectors (cement, ceramics, chemicals, engineering, minerals and ores, non-ferrous metals, steel, water). Therefore, a close collaboration with industry is mandatory to achieve in-depth insights into possible application areas of AI for processes, technology, sensor applicability and assessment of their level of penetration. The overall project approach is based on the development of a 3-dimensional conceptual matrix based on: 1) AI and BG technologies 2) Application areas (activities and industrial processes) 3) SPIRE sectors AI-CUBE's main goal is to define a roadmap in AI and the use of BD for the process industry and their maturity level across the industrial sectors, including guidelines for implementation. Industrial stakeholders and associations will validate the consolidated roadmap ensuring solution feasibility and benefits for the European industrial community. A crosslinked vision over process industry sectors shall facilitate cooperation and boost technologies deployment at their full potential. An in-depth consultation with industry (association, representatives, companies) will provide an overview of current AI and BD algorithms application, identifying exploitable synergies among sectors. A deep study of the application areas in planning and operations within other industrial sectors facilitates a gap analysis, propitiating knowledge sharing among processes and sectors.

A Multi-Actor Multi-Criteria analysis will obtain a widely supported and consensus-based action plan for industrial consultation. This will allow the inclusion of a broad stakeholder community representing the main industry actors throughout all the SPIRE sectors, with which the project consortium has strong connections that will support sector integration and stakeholders' engagement.

3. OBJECTIVES OF THIS DELIVERABLE

The main objective of WP1 is to establish the current technological and industrial landscape regarding AI and BD technologies and process industry sectors in Europe, setting the basis of the following WPs work in defining mapping tools and the roadmap for AI and BD. In order to properly do so, literature reviews and consultation with relevant stakeholders will start from the very beginning of the project. Furthermore, a detailed assessment of both the technological and industrial status will allow to adjust the original implementation plan (if needed), expanding it to additional macro applications areas.

A different focus and context is provided in successive deliverables: D1.1 is a pure technology focus; D1.2 considers technologies in the context of sector and process; D1.3 synthesises findings of D1.1 and D1.2 to define the CUBE dimensions and layout the basis for following WPs 2 and 3. So, in summary, the "Technology" dimension is reviewed in D1.1 and the "Process" dimension is reviewed in D1.2. Finally, in D1.3, the findings of D1.1 and D1.2 are consolidated and used to update the technology and process CUBE dimensions.

The approach and the aim of the activities carried out within Task1.1 is to prepare a report describing an overview of AI and BD technologies and a preliminary picture of their application degree in industrial environments. The deliverable consists of an overview of the AI and BD existing technologies which has been generated by means of literature review, examples of real experiences of participation in AI and BD projects, analysis of existing roadmaps at different levels (regional, national, and international), as well as focused intelligence activity for the identification of the most important research and innovation projects of H2020 and other EU framework Programmes.

A comparison between roadmaps and running projects provides a preliminary picture of how technologies are under implementation and how projects already cover objectives set by roadmaps and strategic research agendas.

A first overall description of the technologies key features, maturity level and applicability will be outlined, providing an adequate starting point for the detailed mapping outlined in WP3 and the roadmap for process industry established in WP4.

We would like to clarify that for the present deliverable, we have not been able as yet to include feedback from stakeholders as the first workshop is pending, and planned to be held in the first half of February. This was agreed by consensus between the partners for several reasons: firstly, it was decided that a sound and well thought out stakeholder engagement strategy needed to be developed and in place before reaching out to stakeholders to provide input to this project (D2.1. Stakeholder engagement strategy, was planned for end October 2020, but delivered with some delay in November 2020), secondly, it will give more to time prepare the workshop and publicity material, contact potential attendees, and carry out follow-up actions; thirdly, the coincidence of dates with Christmas period and availability of potential attendees would make organizing the workshop and guaranteeing its success more difficult; fourthly, aiming at the first week in February will give more guarantees for obtaining quality stakeholders, a more customized audience and will coincide with other Work Packages to serve as input, especially WP2.

4. METHODOLOGY AND APPROACH

In order to compile and review the information contained in this deliverable, we applied a methodology and systematic approach consisting of the following steps:

- **(i)** Define a taxonomy for the technologies of Artificial Intelligence and Big Data. This supplied a more detailed definition for the third dimension of the AI-CUBE. We also defined one of the processes from "product customization" to "product design" which is a more general concept which includes the former.
- **(ii)** Using the taxonomies developed in (i), perform a detailed sector by sector literature search which will be a measure of the current activity in the corresponding processes and AI/BD technologies;
- **(iii)** Perform a literature search on roadmaps and running projects;
- **(iv)** From the results of (ii) and (iii), produce a synthesis and overall vision of the current situation and expected future evolution in the next years.

The keywords indicated in Table 1 were generally used in the literature searches (points (ii) and (iii) above) for all sectors, and any specific aspects, such as which databases/search engines were used, are given in the corresponding sector section. For the literature searches, these groupings allowed for different search combinations of key words from group 1 (AI and BD), group 2 (process application areas) and group 3 (AI/BD enabled technologies), in that respective order.

Table 1 Keyword groupings for literature searches

Group 1 (AI and BD)	**Group 2 (Process application areas)**	**Group 3 (AI/DB enabled technologies)**
• "Artificial Intelligence" • "Big Data"	• "Market trends and open innovation" • "Product design" • "Predictive maintenance" • "Supply chain management (re)configuring and scheduling" • "(Model predictive) process control and optimization" • "Research and innovation management, planning and design"	• "Data understanding and characterization" • "Natural language processing" • "Object and spatial recognition" • "Machine learning" • "Intelligent planning" • "Expert systems" • "Case based reasoning" • "Intelligent agents" • "Cyber-physical systems" • "Data visualisation" • "Data processing" • "Data protection" • "Data management" • "Computing and storage" infrastructure"

The literature reviews were conducted using different search engines and information sources, such as the PNO WheesBee database, including over 115 million of scientific publication, the ISI Web of Knowledge database, Google Scholar, ResearchGate, Scopus, ScienceDirect, ACM, IEEE, among others. Multiple search strings were used applying Boolean logic and combining keyword labels (see Table 1) related to the different layers of categorization applied to the AI & BD technologies (form general to specific labels), related to each sector or industry.

We limited the search to scientific papers published in the last 5 years (2016-2020), mainly specialist journals but also some industry website articles. Occasionally, older articles were also examined, which thematically matched the search space particularly well. The final sample gave a total of 219 papers for all SPIRE sectors, that contribute to a general overview of the main processes in which the AI and BD technologies are applied in the process industry.

5. AI & BD TECHNOLOGIES STATE-OF-THE-ART REVIEW

In this section firstly a glossary is given of the definitions provide the glossary for the AI and BD Technology categories which make reference to the taxonomies given in Figures 1 and 2 Section 5.1). This is followed by a definition and description of the taxonomies themselves (Section 5.2), and by the description of European roadmaps and running projects (Section 5.3). Next, an extensive literature review is documented in Section 5.4 with a European and International scope. Finally, in Section 5.5, several real deployment cases are summarized in an European context.

Note that, as mentioned later, the literature search of Section 5.4 is not limited to only European references, and includes numerous papers from all around the world, where the United States and China are particularly active. We state that this is a true reflection of the real situation, as academic repository and database searches based mainly on technology, process and sector keywords retrieve these results. Also, many publications have co-authors with affiliations from multiple countries around the globe, hence it is difficult to categorize the publications based on geographical region. However, we do include significant EU statistics and references: all of Annex 9.2, Section 6.1 (all European project statistics), Section 5.3 deals exclusively with European projects and roadmaps.

5.1 GLOSSARY OF THE TECHNOLOGY CATEGORIES

Artificial Intelligence

Data understanding and characterization - data characterization can be understood as the summarization of the general characteristics or features of a target class of data. The data corresponding to the user-specified class are typically collected by a query. For example, to study the characteristics of software products with sales that increased by 10% in the previous year, the data related to such products can be collected by executing an SQL query on the sales database. On the other hand, **data understanding** concerns the knowledge you have about data, the needs the data will satisfy, its content and location. Understanding is generally increased as new data is created, used, managed and measured as part of operational processes. *Both (understanding and characterisation) are well related to exploratory data analysis and processing, which employs many tools, concepts and algorithms from statistics, data mining, and machine learning.* Note that this category is one of the least referenced, but is a key pre-activity for many other techniques.

Natural language processing - Natural language processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human language, in particular how to program computers to process and analyse large amounts of natural language data. This data can be in the form of written text (typically unstructured or semi structured, such as a quality control report or management report or a comments/chat section of a web application) or human speech recognition (recorded or in real time). **In digital technology and AI**, a major field is building software which is able to emulate and respond as a human would do in written text or speech, in an interactive way. *This has clear application in process industries for machine control, interactive robots, and automatic synthesis and information retrieval of industrial information captured in a textual form (e.g. reporting).* Note that this category is one of those with the least references, however “speech recognition” is becoming a key component of automated systems.

Object and spatial recognition – Is a computer technology related to computer vision and image processing that deals with detecting and recognising instances of semantic objects of a certain class (such as humans, buildings, or cars) in digital images and videos. Spatial recognition deals with locating the objects in some spatial reference, such as an “x, y, z” coordinate or "bounding box". This technology has important applications for industrial robots and autonomous vehicles (which are increasingly used in warehouse and storage installations). It can also be applied for recognising objects and components during "picking". Specific applications are SLAM (Simultaneous localization And Mapping) which is typically used for self-driving vehicles and collaborative robots, and is key for guaranteeing human safety in real time systems. This is done by data fusion from different types of sensors (depth cameras, infra-red, laser, radar, ..).

Machine learning – Is the study of computer algorithms that typically train/build data models which can learn from a historical dataset and thus are said to “learn from experience” represented in the data. ML is considered a sub-area of Artificial Intelligence. *ML algorithms are used in a wide variety of applications, such as computer vision, process simulation and predictive maintenance, where conventional algorithms and approaches cannot be applied or produce insufficient quality, due to different reasons such as the stochastic, non-linear nature of a system, or a significant “noise” presence in the data.* Three main categories of ML are **“supervised learning”** (known historical results/labels exist), **“unsupervised learning”** (no labels are available for training) which can use pattern matching to discover underlying structures and **“reinforcement learning”** where a “teacher” is in the loop (which may be human or another algorithm) to give “reward” feedback for correct decisions. Another important and more recent type of ML is **“deep learning”** which uses artificial neural network algorithms with many layers (hence the “deep”). *Applications include: computer/machine vision, speech recognition, natural language processing, audio recognition, machine translation, bioinformatics, image analysis, material inspection, among others.* Note that this category has the highest number of references, which could be due to its use as a generic term to cover different types of applications: supervised, unsupervised, different types of approaches, and so on.

Intelligent planning – Also known as "artificial intelligence planning" or "automated planning" and scheduling is a branch of artificial intelligence that concerns the use of algorithms to execute strategies or action sequences to carry out a series of steps to achieve one or more goals. On the one hand, there is the **real time control aspect**, typically for execution by intelligent agents, autonomous robots and unmanned vehicles, where the solutions are complex and must be discovered and optimized in multidimensional space. On the other hand, there is the **optimal resolution of complex management planning problems** (typically over time), such as production planning, supply and demand, conditional and contingency planning, where often there are “probabilistic” aspects and “constraint satisfaction” to take into account.

Expert systems – Computer systems which emulate the decision-making or diagnostic ability of **human experts**. They are designed to solve complex problems by reasoning through bodies of knowledge, represented mainly as **“if–then-else”** rules instead of conventional computer code. Expert systems were one of the first “success stories” of AI in terms of **deployment** to solve real problems, however one key drawback was knowledge acquisition from human experts to define the “expert rules”. In contemporary systems, human expert rules are combined with data drive models and rules extracted directly from data. **An expert system is divided into two subsystems: the inference engine and the knowledge base.** The knowledge base represents facts and rules, whereas the inference engine applies the rules to the known facts to deduce new facts. *They have many reported applications in process industries, such as for complex process control, setting calibration parameters, predictive maintenance and diagnosis, among others.*

Case based reasoning – Is the process of solving new problems based on the solutions of similar past problems. *For example, a technician who fixes an industrial machine by remembering how s/he fixed another machine that exhibited similar symptoms is using case-based reasoning. Also, an engineer who consults a chemical reactions database may be using analogy in order to adapt existing knowledge to new solutions.* CBR is an example of analogy solution making which humans commonly use every-day to solve problems. CBR has four key steps which are implemented as a computer application: **"Retrieve"** (obtain previous cases), **"Reuse"** (adapt previous case to new situation), **"Revise"** (test and further adapt as necessary), **"Retain"** if the new adapted case has resulted effective, store it for future use. Note that this category does not have so many references but could be a key approach for many areas.

Intelligent agents – In general refer to a set of processes (which are typically asynchronous) which interact between themselves and with the environment in an "intelligent" manner, in order to achieve some goal. Individually, they can be very simple or complex, depending on the application. *A simple example would be an industrial sensor which monitors/observes a process and if the temperature and/or pressure go out of a given range, take some remedial action. So this would be programmed as a simple rule:* **"if condition, then action".** More complex interactions and behaviour between states can be represented, for example, by a Markov state diagram, and the overall objective will be to **maximize or minimize a "utility function"**, "objective function", or "loss function". **Multi-agent systems** (i.e. hundreds or more of agents) can also be used to simulate competing systems (such as supply/demand) to find an optimum equilibrium. Note that this category does not have so many references but could be a key approach for many areas.

Cyber-physical systems – Are systems in which a mechanism is controlled or monitored by computer-based algorithms. In contrast to traditional embedded systems, a CPS is typically designed **as a network of elements that interact with each other** via physical inputs and outputs, related to the fields of **robotics and sensor networks**, which are controlled and supervised by intelligence mechanisms typical of the field of artificial intelligence. *Example applications are: collision avoidance, nano-technology manufacturing, industrial control systems, robotics systems, operation in dangerous or inaccessible environments, sustainability (e.g., zero-net energy buildings), and enhancement of human capacities (e.g., exoskeletons), industrial plant security/surveillance/maintenance.* Robotics is not currently a key technology for process industries (more for manufacturing) but human safety considerations will drive future growth for self-driving vehicles/machines, collaborative robots, etc.

Big Data

Data visualization - is an interdisciplinary field of study whose object is the representation of data in graphical format. As a form of communication, it is particularly efficient when the amount of data to be represented is large, for example in the case of time series and/or Big Data. *Key applications include "dashboard" displays for complex process real-time control systems, and management decision support systems.* Note that this category is a key element for data understanding.

Data processing – in general, deals with the collection and manipulation of items of data to produce meaningful information. It may involve various processes, including: **validation** (ensuring that supplied data is correct and relevant), **sorting** (arranging items in some sequence and/or in different sets), **summarization** (reducing detailed data to its main points), **aggregation** (combining multiple pieces of data), **analysis/interpretation**, **reporting** and **classification** (separation of data into various categories). Note that this category is a basic aspect of many other categories.

Data protection - data protection is the relationship between the collection and dissemination of data, technology, the public expectation of privacy, and the legal and political issues surrounding them. It is also known as data privacy or information privacy. In industrial terms it can be related to cyber-security and the protection of installations from cyber-attacks, as well as industrial secrets, patents and confidentiality. In the European context, the General Data Protection Regulation (EU) 2016/679 (GDPR) is a regulation in EU law on data protection and privacy in the European Union (EU) and the European Economic Area (EEA). Its primary aim is to give individuals control over their personal data and to simplify the regulatory environment for international business by unifying the regulation within the EU. Note that this category currently has the least references, however it is a key strategic issue identified for industrial installations, related to cyber-security. So it is a potential big growth area for process industries as digitalization progresses.

Data management - comprises all disciplines related to managing data as a valuable resource. In a digital context, it offers tools to facilitate the management of data and improve performance, consisting of an integrated, modular environment to manage enterprise application data, and optimize data-driven applications over its lifetime. It includes the following objectives: produce enterprise-ready applications faster; improve data access, speed iterative testing; automate and simplify operations; support business growth.

Computing and storage infrastructure - provides the hardware and services that other systems and services are built on. It has different components and some of the key ones are listed as follows: file and disk storage service such as file servers, file backup, long-term archive and ftp services; networks; authentication, the means by which users log in and identify themselves; authorisation by which a service determines whether an authenticated person should have access to that service; virtual hosting to provide a managed platform for hosting Windows, Linux and Unix services on a reliable virtualisation platform; cloud computing services to provide a platform to self-provision server infrastructure to support both employees and clients.

5.2 DEFINITIONS AND TAXONOMIES

5.2.1 Artificial Intelligence

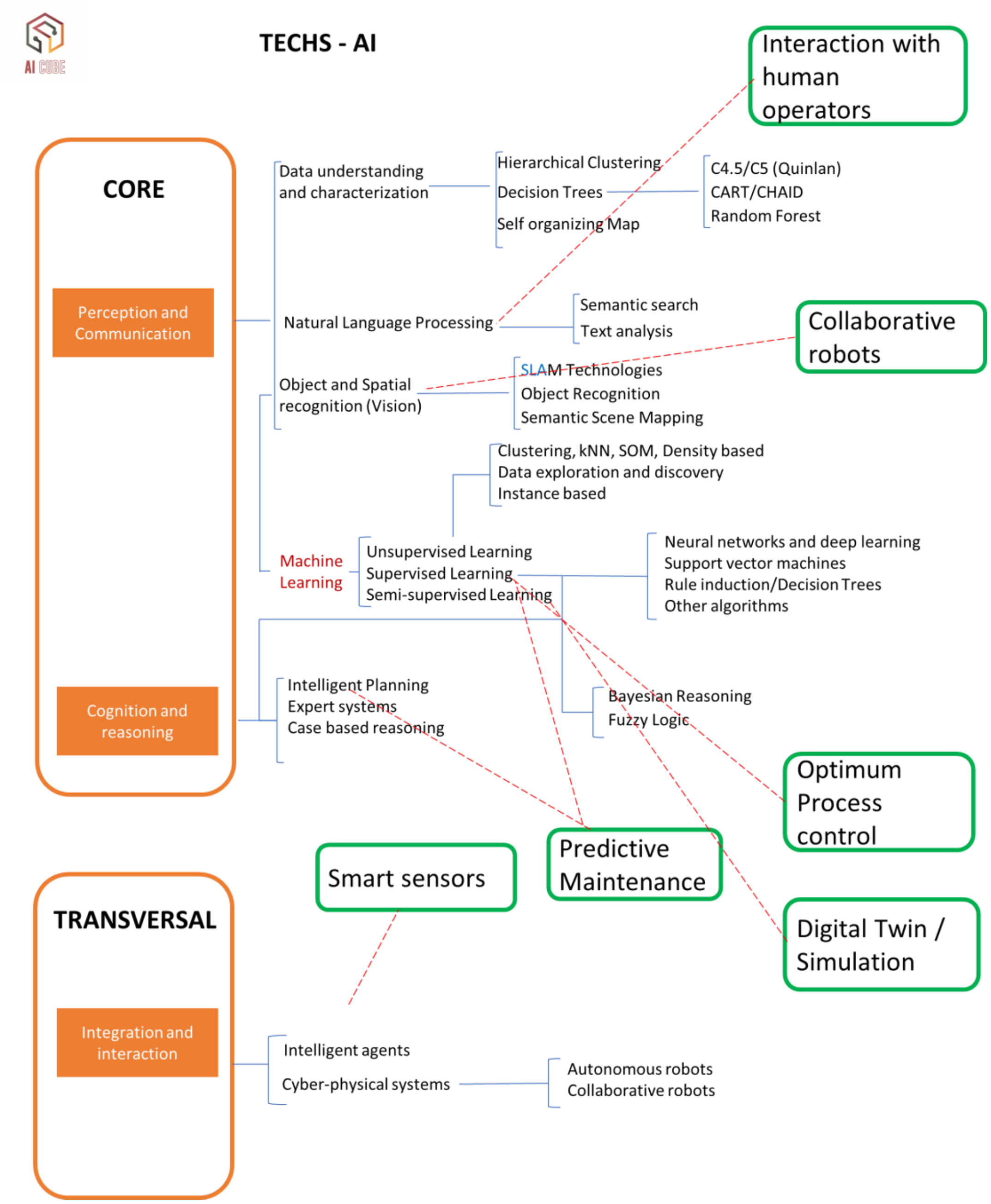

Figure 2. Artificial Intelligence Taxonomy

5.3.2 Big Data

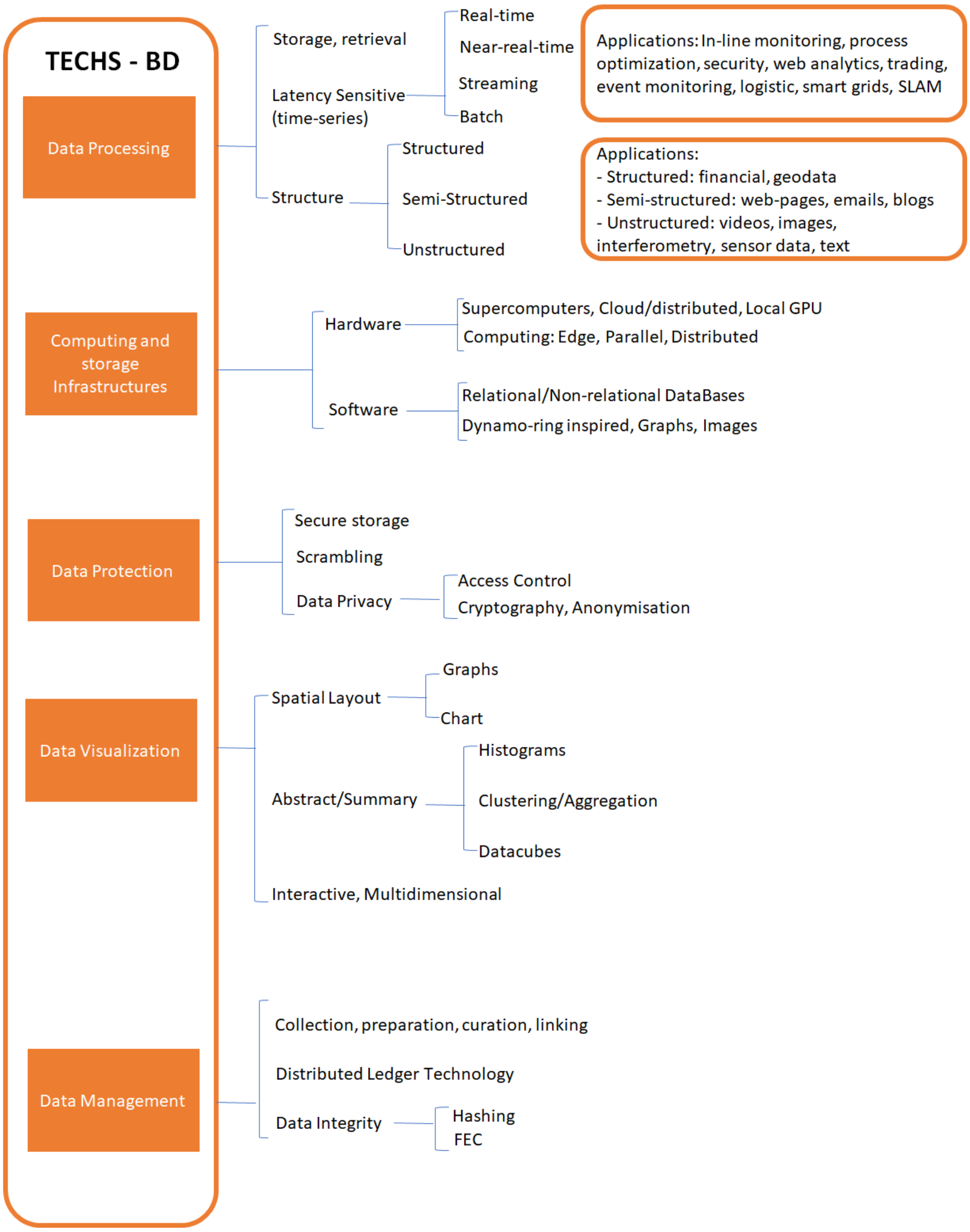

Figure 3. Big Data Taxonomy

Figures 2 and 3 illustrate two taxonomies developed specially for AI-CUBE and which take into account current state of the art taxonomies, such as the one developed by the EC AI Expert group [1], which has been customized for SPIRE and process industries of the AI-CUBE project. Other example AI taxonomies evaluated include [2,3,4,5,6].

In Figure 2 it can be seen that the top level on the left is divided into two main CORE categories (perception and communication, cognition and reasoning) and one TRANSVERSAL category (interaction). At the second level of the AI taxonomy, four categories are defined and one transversal (machine learning). Some example applications are indicated in the green outlined text towards the right. In Figure 3, five top level DB categories are shown on the left, and the subcategories can be seen to be mainly hardware and software related. Some example applications are indicated in the orange outlined text on the top right. Example BD taxonomies evaluated include [7,3,4,5,12].

5.2.3 Categorization of Artificial Intelligence

With reference to Figure 2, the AI taxonomy has two core categories, “perception and communication” and “cognition and reasoning” and one transversal category “integration and interaction”. The overall idea of the categories is to holistically represent the functionality an “intelligent agent” which perceives, thinks, then acts/interacts with its environment. In this way the categorization will be relevant to any situation.

A) Perception and communication

This category has four main groupings of sub-categories and one (sub) transversal theme (machine learning): data understand and characterisation, natural language processing, object and spatial recognition (Vision). In this way we group the main ways of receiving and transmitting information. We distinguish between data modelling (machine learning) on the one hand, and data exploration (in the form of data understanding) as a necessary prerequisite to the data modelling stage. In fact, from real use cases it can be seen that the end objective of a project can be to better understand a problem through data analysis/exploration. This phase includes non-supervised techniques such as clustering, as well as “white box” supervised learning such as rule induction, which may be combined with the clustering. One typical situation of data gathering in a process industry infrastructure is through in situ sensors which capture real time data and pass it to the monitoring and control functions.

B) Cognition and reasoning

This category has three sub-categories and again the (sub) transversal theme of machine learning: Intelligent planning, expert systems, case-based reasoning. Again, these themes are curated for process industries and practical/deployable applications. One information is received by the perception capabilities, the cognitive faculties formulate actions to be performed based on this information, and then transmit these actions in some way to the exterior. For example, based on the sensor data captured by the perception functions, the process optimization function could decide to increase the production rate. Also, predictive maintenance can be performed by identifying sensor anomalies. A “digital twin” will be built from sensor data but also from supervised learning, for example.

C) Machine learning

This category is ubiquitous in perception and cognition, where techniques can be divided loosely into "black box" such as neural networks and "white box" such as rule induction. In order to perform supervised learning, the examples and counter examples for training need to be labelled. Sometimes it is not possible to label all the examples (semi-supervised) or any at all (unsupervised).

D) Integration and interaction (transversal)

Some major paradigms or systems are considered "transversal" to perception and cognition, for which we have included "intelligent agents" and "cyber-physical systems" (e.g. robots, but not limited to). "agents" have a perception component and interact with their environment, but also have a cognitive/reasoning capacity. This is also similar for industrial robots, for example, SLAM technology allows the robot to interact with its environment and a cognitive layer (which can be in a local server) evaluates and plans the actions to do).

5.2.4 Categorization of Big Data

With reference to Figure 3, the BD taxonomy has five core categories, "data processing", "computing and storage infrastructures", "data protection", "data visualization" and "data management". This has some similarities to the BDVA categorization, with adaptation for the specific context of SPIRE process industries. Note we have excluded data analytics as we considered this overlapped too much with Artificial Intelligence where it is already covered. We have included computing infrastructures, as this may or not be an issue for specific use cases: it may have outsourced but it also may be in-house.

A) Data processing

This has three main groupings of sub-categories: storage and retrieval, latency sensitive and structure.

B) Computing and storage infrastructures

Firstly, this category is divided into hardware and software, then into remote/local hardware and relational/non relation databases and storage for some specific data types such as graphs and images.

C) Data protection

This category covers both secure storage (i.e. backup copies, legacy requirements, etc.) as well as privacy (i.e. prevent unauthorized access, anonymize so that when transmitted it cannot be read, etc.).

D) Data visualization

Visualization is a key aspect of data browsing and exploration, for example statistical summaries of plots, histograms, pie charts, as well as multi-dimensional visualization for data retrieved and aggregated by different criteria.

E) Data management

This differentiates from data processing as the latter is considered a lower level of (raw data) processing whereas data management deals with a higher meta-level with business meaning. We also include ledger technology here as well as data integrity (for example, after/before processing/transmission, etc.).

5.3EUROPEAN ROADMAPS AND RUNNING PROJECTS

5.3.1 Roadmaps at European Level –Scientific and technological

A comparison between roadmaps was performed to provide a preliminary picture of the most important R&D topics set by roadmaps and strategic research agendas at European level. Taking into consideration that AI and BD technologies can cover different fields and industries, at this step roadmaps from discrete manufacturing, process industry, logistics and ICT sector were analysed to create a more complete map of the most important topics for the development of these technologies (the complete list of roadmaps is available in the appendix). The roadmaps cover different time horizons, from 2025, to 2030 and 2050.

For **discrete manufacturing,** in the new version of the “EFFRA vision document” (2019), different headlines have been identified to exploit the vision of co-creation through manufacturing eco-systems. The key headlines are: excellent, responsive and smart factories; low-environmental footprint, customer-driven value networks; parallel product manufacturing engineering; human-driven innovation. For each of these areas different priorities were listed, supported by the implementation of AI and BD technologies as for example the need for “agile and robust optimal manufacturing” to respond quickly to changing customer demands, fluctuating characteristics of raw materials or components; or “virtual end-to-end lifecycle engineering from product to production lines, factories and networks”. AI can accelerate the design and engineering processes, enable design for life-cycle, and at the same time, increase the productivity of engineers, designers, material scientists, and decision-makers, and shorten time-to-market and make better products.

In the document vision of ManuFUTURE (2019), a factory becomes a complex, lifelong and highly integrated system, which operates in the “room of parameters” for best performance and zero defects. The research domains identified are: “processes and technologies”, “digital transformation” (which includes: quality in production system, dynamic and flexible production systems, digital-real convergence in production systems end ecosystem), “robotics and flexible automation”, “nano-technologies and materials”. One priority suggests the introduction of the equipment and production lines that integrate the self-monitoring, self-assessment, self-learning and self-adjusting concepts of AI at the shop floor level, allowing achieving re-configurability, remote operations and optimisation for production systems. Moreover, deep learning or other machine learning techniques will enable the creation of models to support quality-related tasks, such as anomaly detection, fault detection and classification, product quality control. Moreover, new tools are needed to enable CPS (Cyber-Physical Systems) to promptly adapt process plans, parameters and production based, all on the needs of the value chain. Another priority is “marrying” the signals with simulation models and linking different data sources to obtain a digital representation of product and processes which is reliable and constantly updated. Moreover, the development of neurocognitive approaches will enable the collection, transfer and analysis of various forms of data, processes, and workflows within the manufacturing to make smart decisions in real-time in collaboration with the humans, allowing a smooth and safe human-machine interaction.

For the **ICT sector**, we considered roadmaps provided by: ARTEMIS (in 2016), Aeneas-Artemis-EPoSS (in 2019) and Big data Value Association (2020)

The first one aims to support a vision where Europe remains among the leaders in the area of CPS and Embedded Intelligence since CPS is a major enabler of the Digital transformation and for the 'Digitisation of Industry'. Between the research priorities and challenges identify in ARTEMIS's roadmap, there is the need for the development digital platforms that incorporate CPS focusing on building services in smart spaces and promoting the interoperability of CPS as objects or nodes in Internet. The need is also highlighted for developing autonomous and cooperative systems with safe and robust environmental perception, adaptive behaviour and advanced mobility and manipulation capabilities. CPS should be able to increase their level of automation and their decision-making capabilities also for the handling of uncertainty; the goal, in particular in safety-critical environments - includes 24/7 reliability, with 100% availability, and 100% connectivity, in addition to the real-time response. Moreover, new techniques and tools are needed for the optimisation of heterogeneous models with multiple objectives stemming from different application and engineering domains as well as across the supply chain.

The roadmap "Electronic Components & Systems (ECS)-Strategic Research Agenda 2019" by Aeneas-Artemis EPoSS aims to foster the digital transformation by supporting the development of technology solutions over the entire ECS value chain, addressing the emergence of new business models with shorter innovation cycles and new transaction mechanisms for improving trust and security. The work focuses on a set of 5 key applications areas (digital life, digital industry, energy, health and well-being, transport and smart mobility), and 5 essential capabilities (architecture, design and integration, connectivity and interoperability, safety, security and reliability, computing and storage, process technology, equipment, materials & manufacturing for ECS). Even though the roadmap refers to the ICT sector, it provides some priorities that are similar to the ones proposed for example by ManuFUTURE. The implementation of AI and BD will make it possible to detect anomalies or similarities, to optimise parameters and to create decision-making support tools which can indicate warnings on-line before damage can occur. Among the priorities there is the need for developing digital twins and simulation models for the evaluation of product life-cycles and of industrial assets at all factory levels. Moreover, digital platforms should be developed to integrate sensors and actuators with the aim of using data analytics in different applications such as precision medicine and personalised healthcare and wellbeing.

One of the most recent roadmaps for the ICT sector is the one presented by the "Big data Value Association". The document unifies the strategic focus of each of the three disciplines engaged in creating the Partnership on AI, Data and Robotics. The first horizontal priorities are linked to the innovation of ecosystem enablers: skills and knowledge, data for AI and experimentation and deployment. It is necessary to work towards the alignment of curricula and training programmes for AI, Data and Robotics professionals, with industry needs and also develop short-courses aimed at decision-makers in industry and public administration, and those wishing to upgrade or acquire AI, Data and Robotics based skills. Moreover, the need is highlighted to promote open datasets and new open benchmarks for AI algorithms, subject to quality validation from both software engineering and functional viewpoints and, at the same time, create the conditions for the development of trusted European data sharing frameworks to enable new data value chain opportunities. Finally, it is important also to establish AI, Data and Robotics large scale demonstrators aligned to European industry needs, and to stimulate cooperation between all stakeholders in the value chain around experimentation and deployment of these technologies. In the provided framework 5 cross sectorial technology enablers were identified: sensing and perception, knowledge and learning, reasoning and decision making, action and interaction, systems methodologies, hardware and tools. For each of these enablers, different research priorities (we considered the long term priorities) were suggested, as for example: new materials and processing techniques will yield new forms of sensing and data acquisition and also the development of self-configuring and adaptive sensors. The research will also allow the incorporation of environmental changes in the adaptive decision-making tools that will further support the human interrogation, the social interaction and mental models. Other needs are related to the development of intrinsically secure and privacy-preserving algorithms, the automated testing and soft validation of systems, including physical systems able to guarantee regulatory compliance. The new autonomous learning approaches have to be safe especially if used in critical applications and need to assure a complex collaborative interaction between multiple agents.

From the **logistics sector,** we have analysed the last roadmap ALICE (2019) that focuses on the freight transport and GHG emissions and whose objective is the decarbonisation of the sector. The solutions that directly lead to emission reductions were clustered into five groups: “freight demand growth is managed”, “transport modes are smartly used and combined”, “fleets and assets are shared and used to the max”, “fleets and assets are energy efficient”, fleets and assets use lowest emissions energy sources feasible. In the first 4 groups, we have identified some research priorities that propose the implementation of AI and BD technologies. For managing growth in freight transport demand, the restructuring of the supply chain implies the redesign of logistics network’s nodal points and inter-related transport flows to minimise distances and optimise load factors; another solution can be the decentralisation of production and stockholding that requires to move the production stockholding and sales closer to consumers and an optimal management of inventory. The solutions that use and combine the best transport modes include the combination of different linkages providing better access to, and optimising transhipment possibilities and offering to the customer (shipper or forwarder) an integrated solution for its (inland) transport. For sharing and maximizing the use of fleets and assets, load optimization is proposed in order to adjust truck size to the load and optimise the use of the vehicle space, as well as the load consolidation. Moreover, solutions include the possibility of a different approach in which flows from different stakeholders are combined (i.e. multi supplier-multi-retailer) that require dynamic planning and the arrangement of multiparty transport flows and inventory management via shared hubs and warehouses. Finally the creation of efficient fleets, as well as autonomous trucks and rail services are proposed.

For what concerns the **process industry**, the VERAM roadmap (2018) addresses key needs of minerals, metals, aggregates and biotic raw materials and provides actions throughout the entire cross-sectorial raw materials value chain from primary raw material exploration, extraction, management, harvesting and transformation, and the valorisation of waste into secondary raw materials closing the material flows and the development of new products and applications. In particular, the deployment of new technologies integrating AI and BD solutions, will not only contribute to a more resource-efficient production but allow raw materials input to be brought into a new era of customised manufacturing, imposed by environmentally-conscious customers and shifting market demands towards carbon neutral processes. The roadmap highlights also an issue linked to the increase of automation and artificial intelligence that will drive demand for ore technologies and with it more materials. Potentially, this can lead to temporary or longer-term shortages which might need substitution strategies. The substitution of high-value materials can be achieved by developing applications with an equivalent technology that does not rely on the same raw materials.

For what concerns the SPIRE roadmaps (2016-2018), the first version includes a review of new technologies, technologies associated with water, development and implementation of scrap sorting, technology and processes, batteries, filtering impurities, among others. It is indicated that data processing and cloud technology could be useful tools for further development of novel LCA (Life Cycle Inventory) approaches. Other key issues include: scale up, market acceptance, commercialization, cross-sector and tech-transfer. Indeed, the innovation required in conceptualization and innovation seems a fertile ground for leveraging automated knowledge gathering, synthesis and processing.

The last release, in 2018, presents the vision towards 2050 and it foresees an integrated and digital European Process Industry, delivering new technologies and business models that address climate change and enable a fully circular society in Europe with enhanced competitiveness and impact for jobs and growth. In the document, there is only one direct reference to AI and BD technologies as enabler for the smart integration of process industries, boosting process efficiency, generating new business models and making sure that European value chains and related data remain in Europe. In general, the digitalisation, and therefore the implementation of AI and BD, is identified as a transversal topic with the industrial symbiosis to support and accelerate the transformation towards resource and energy efficiency. In particular, in the field of process control, digital technologies (through data collection, data storage and extraction of new information) help to provide detailed insights into resource availability, use and quality, up to the level of each individual user. They will further contribute to optimise production yield, enhance resource flexibility and accelerate synergies between sectors and with energy suppliers, through the development of platforms, databases, and advanced near real-time decision support systems.

In June 2020, SPIRE presented also a proposal for a European Partnership under Horizon Europe called *Processes4Planet*.This initiative aims at developing and deploying the innovations for a profound transformation of the European process industries to make them circular and achieve overall climate neutrality at EU level by 2050, while enhancing their global competitiveness. Through cross-sectorial technological and non-technological innovation efforts, and an integrated approach on climate and environmental issues, *Processes4Planet* will achieve three general objectives:

- Developing and deploying climate-neutral solutions,
- Closing the energy and feedstock loops,
- Achieving a global leadership in climate-neutral and circular solutions, accelerating innovation and unlocking public and private investment (competitiveness).

Processes4Planet will work on emerging technologies and on the scaling up of technologies already developed at higher TRLs to deliver expected CO_2 emission reductions by 2030 and to achieve its full impact by 2050.

In particular, in this roadmap five specific objectives have been identified: (i) integrating renewable energy; (ii) reduce emissions through CO/CO_2 capture and use; (iii) Ensure full circularity and overhaul the use of waste; (iv) Moving towards commercially viable climate neutral and circular industry solutions; (v) Fostering new skills & jobs and reducing barriers for market uptake. The digitalisation (i.e the adoption of digital technologies as AI and BD) is considered as an innovation area that will lead all the specific objectives through six innovation programmes, which are:

- Digital materials design
- Digital process development and engineering
- Digital plant operation
- Intelligent material and equipment monitoring

- Autonomous integrated supply chain management
- Digitalisation of industrial-urban symbiosis

5.3.2 Political initiatives at European, Country and Regional Level

The European Commission white paper (Feb. 2020) "On Artificial Intelligence - A European approach to excellence and trust" recommends, among other aspects: (i) keeping accurate records regarding the data set used to train and test the AI systems, including a description of the main characteristics, how the data set was selected and when necessary, the datasets themselves; (ii) Documentation on the programming and training methodologies, processes and techniques used to build, test and validate the AI systems, including where relevant in respect of safety and avoiding bias that could lead to prohibited discrimination.

In the workshop report "The European AI Landscape", the strongest AI regions within the EU were identified as the UK, Germany and France. The top 10 AI start-up hubs within the EU were identified as London, Berlin, Paris, Madrid, Stockholm, Amsterdam, Copenhagen, Barcelona, and Dublin. It was cited that European AI start-ups raised EUR 3.6 billion in 2017, almost three times more than in 2016. The top 5 industries they operate in were identified as: Financial technologies; health technologies; marketing, advertising and technology; business intelligence; automotive. It was found they focus mostly on B2B (business-to-business), which represents 76% of the total compared to 24% for B2C (business-to-consumer). Hence, it is clear that process industries are currently not a prime focus for AI technologies according to this report, and in a global assessment.

The High-Level Expert Group on Artificial Intelligence (AI HLEG)[1] is a group of 52 experts, founded by the European Commission after the launch of its Artificial Intelligence Strategy in 2018. The aim of this high-level group is to sustain the implementation of the community strategy. The members were selected following an open selection process and comprised representatives from academia, civil society and industry.

The AI HLEG worked on 4 main deliverables:

1. **Ethics Guidelines for Trustworthy AI:** the document puts forward a human-centric approach on AI and lists a set of key requirements that AI systems should meet in order to be Trustworthy.
2. **Policy and Investment Recommendations for Trustworthy AI:** building on its first deliverable, the group has put forward a list of recommendations that can guide Trustworthy AI towards sustainability, growth and competitiveness, as well as inclusion – while empowering, benefiting and protecting human beings.
3. **The final Assessment List for Trustworthy AI (ALTAI):** a practical tool that translates the Ethics Guidelines into an accessible and dynamic (self-assessment) checklist. The checklist can be used by developers and users of AI who want to implement the key requirements in practice
4. **Sectoral Considerations on the Policy and Investment Recommendations:** the document explores the possible implementation of the recommendations, previously published by the group, in three specific areas of application: Public Sector, Healthcare and Manufacturing & the Internet of Things.

[1] https://ec.europa.eu/digital-single-market/en/high-level-expert-group-artificial-intelligence

The AI HLEG has worked closely with the European community of AI stakeholders through the AI Alliance. Through a number of ad hoc consultations, the members of the AI Alliance (4000 representing academia, business and industry, civil society as well as EU citizens and policymakers) offered detailed feedback for the Ethics Guidelines for Trustworthy AI.

In the case of **France,** the main objectives of the French AI strategy are to: (i) Improve the AI education and training ecosystem to develop and attract the best AI talent; (ii) establish an open data policy for the implementation of AI applications and pooling assets together; (iii) develop an ethical framework for a transparent and fair use of AI applications. Key players in France include: INRIA, 3IA (Interdisciplinary institutes on Artificial Intelligence, “3IA Côte d'Azur” project led by the Université Côte d'Azur, PaRis Artificial Intelligence Research InstitutE (PRAIRIE) and the Artificial and Natural Intelligence Toulouse Institute (ANITI) led by the University of Toulouse.

In the case of **Italy,** the National Strategy on AI (presented in August 2019) has as key objectives: (i) Improving AI-related skills and competences at all education levels and creating lifelong learning and reskilling opportunities for the labour force; (ii) Fostering AI research and innovation to enhance the competitiveness of the entrepreneurial ecosystem; (iii) Establishing a regulatory and ethical framework to ensure a sustainable and trustworthy AI; (iv) Supporting (international) networks and partnerships; (v) Developing a data infrastructure to fuel AI developments; (vi) Improving public services through a wider adoption and use of AI applications. Key players in Italy include: AIIS (Artificial Intelligence and Intelligent Systems Laboratory), Italian Interuniversity Consortium for Informatics (CINI), Italian Institute of Technology (IIT) and Institute for Calculation and Networks for High Services (ICAR) of the National Research Council (CNR).

Germany’s Artificial Intelligence strategy includes the following points: (i) Guaranteeing a responsible development and deployment of AI which serves the good of society; (ii) Integrating AI in society in ethical, legal, cultural and institutional terms in the context of a broad societal dialogue and active political measures. Key players/potentiators include: Gruender platform: online platform to support start-ups, Industrial Collective Research programme fostering joint business and science research on collective AI projects, advisory and funding services to foster the growth of AI start-ups (e.g. EXIST focusing on university spinoffs) through for instance venture debt (e.g. Tech Growth Fund), AI Competence sectors (4 or 5 in different regions), research institutes and universities.

The **Spanish** national plan for Artificial Intelligence was recently unveiled (2nd December). To summarize, it said that three factors were driving growth of AI: greater availability of data, development of hardware with more processing and storage capability, and improvement of algorithms. Example AI application areas were given as: automated translation, voice recognition, healthcare, medical diagnosis, pharma, drug discovery, cyber security and industrial optimization strategies. A plan consisting of seven points was given: excellence in innovation, potentiate use of Spanish language in AI, create employment, transform industrial production, generate confidence in AI for citizens, ethical framework, socially inclusive/gender equality and sustainability. With respect to the economic budget for AI, there will be an initial public allocation of 275M€, and a commitment of 600M€ in the period 2021-2023, which includes a fund called #NextTech. It is expected that this public funding will kick start private investment estimated in 3.3B€.

5.3.3 Mapping of running European projects

During the finalization of the taxonomies for AI and BD, in order to analyse the applications and the ongoing research of these technologies, a map of the European projects was performed.

This analysis was conducted on the Cordis database selecting the projects from ICT, FoF and SPIRE calls under the H2020 work programme. In fact, given the objective of AI-CUBE project, the considered calls represent one of the most important and updated dataset of information on the ongoing European effort on the development of AI and BD technologies and therefore a good start point to identify the gaps which AI-CUBE roadmaps could cover.

The first step of the mapping aimed to extract the projects, which have developed an application or a new functionality for the technologies, using two lists of keywords (one related to BD and one to AI) for the search queries. The search was limited to the title and the abstract of the projects that summarizes the main objectives and working steps. The keywords were the following:

- List 1:
    1. Big data
    2. Data management
    3. Business analytics
    4. Big data analysis/analytics
    5. Computer infrastructure
    6. Storage infrastructure
    7. Real time
    8. Distributed ledger

- List 2
    1. Artificial intelligence (AI)
    2. Machine learning
    3. Cognition/reasoning
    4. Natural language processing
    5. Deep learning
    6. Cyberphysical systems (CPS)

With reference to Table 2, the keywords allowed to identify about 300 projects out of 1500. Even though the number of projects in the ICT calls is higher than in the other two calls, it is possible to observe that the percentage of projects (already closed or running) dealing with AI and BD topics is quite similar; this means that the European effort for these technologies focus not only on their development (ICT sector) but also on their application in different industries.

Table 2 Statistics for different types of European project calls

Calls	**N° of projects**	**N° of projects with identified keywords**
ICT (+IoT)	1287 (15 from IoT calls)	265 (20,5%)
FoF	145	26 (18%)
SPIRE	80	12 (15%)
Total	*1512*	*302*

The second step of this activity was related to the analysis of the selected projects in order to assign each of them to 6 process macro-areas identified in Section 4: market and open innovation, product design, predictive maintenance, supply chain management (configuring and scheduling), process control and optimization, and research and innovation management. The aim of this step was to identify the main applications of the projects and to start the creation of the state of the art of each of the technologies, in order to build the cube.

Table 3 European project call type vs type of action

Calls	N° of projects	RIA	RIA %	IA	IA %	other
ICT	265	130	49%	74	28%	63
FoF	26	13	50%	12	46%	1
SPIRE	12	4	33%	7	58%	1

Table 3 shows that most of the projects in the three calls are research and innovation actions (RIA) meaning that these technologies are still in the first step of development and application. This highlights that the spreading of AI and BD in industry sector has commenced in recent years and cross-sectorial fertilization is needed in order to increase the use of these technologies which will play a key role in increasing the competitiveness of European companies and supply chains

Given the high number of projects from ICT calls, this step was performed only for a set of 20 projects directly linked to the manufacturing and process industries. In fact, the ICT research concerns different industries, areas and disciplines from discrete manufacturing through to biology or medicine or entertainment.

It is possible to highlight that some of the ICT projects do not refer to a specific process but are mainly focused on the technology development. For example, the project “knowlEdge” (ICT-38-2020) aims at developing a new generation of AI methods, systems and data management infrastructure. The framework will provide means for the secure management of distributed data and the computational infrastructure to execute the needed analytic algorithms and redistribute the knowledge; this project will have 3 industrial cases from manufacturing but it is not explained how this framework will be applied.

For what concerns the FoF calls, the main objective of the projects is related to the optimization and monitoring of the production process and often, in each project, there are more than two pilot cases which will demonstrate the application of the technology in different sectors. The automotive, machinery and aerospace sectors are the most common but there are industrial cases also from railway, white goods, tyre, footwear and others sectors.

Also the industrial cases defined in each of the SPIRE projects come from different sectors: steel and chemicals are the most frequent industries chosen to demonstrate the improvements and the new functionalities of AI and BD technologies, followed by ceramics, minerals and non-ferrous metals.

In the following list a brief abstract of the main objectives of the 11 SPIRE projects is provided[2]

COGNITWIN: this project aims to develop models with cognitive capability for self-learning and predictive maintenance which will lead towards optimal plant operations.

ProPAT: the project implements smart sensors for measuring different process parameters, such as temperature, flowrate, pressure, etc., and integrates them into a versatile global control platform for data acquisition, data processing & mining and User Interface in order to measure properties of process streams and products accurately and in real-time.

[2] The SPIRE project n° 12 is AI-CUBE which is not included in the list

COGNIPLANT: this project will develop digital-twin and advanced analytics to improve a production plants' performance and monitor energy and resource consumption.

FUDIPO: aims at developing a set of tools for diagnostics, data reconciliation, and decision support, production planning and process optimization tools including model-based control.

iCAREPLAST: addresses the cost and energy-efficient recycling of a large fraction of today's non-recyclable plastics and composites from urban waste with the use of AI predictive control and real time optimisation

CAPRI: this project will develop, test and experiment an innovative Cognitive Automation Platform (CAP) for Process Industry Digital Transformation, enabled by cognitive tools that provide existing process industries flexibility of operation, improvement of performance across different indicators and state of the art quality control of its products and intermediate flows.

FACTLOG: the project will combine digital twins, which are driven by domain models (i.e. knowledge), with the models derived from data (i.e. experience); a real-time processing layer will be implemented where observations (i.e. events), knowledge and experience interoperate to understand and control the behaviour of a complex system (i.e. cognition).

COCOP: this project aims to implement a concept that integrates existing industrial control systems with efficient data management and optimisation methods and provides means to monitor and control large industrial production processes. The plant-wide monitoring and control incorporate computationally intensive data analysis and large scale optimisation.

INEVITABLE: this project will develop a high-level supervisory control system for different production plants to be demonstrated in operational environments to enable autonomous operation of the processes based on embedded cognitive reasoning.

HyperCOG: this project will apply some of the latest advances in AI such as modelling for twin factories, decision-support systems for human-machine interaction and augmented reality for industrial process visualization. It pursues self-learning from the process in order to deal with the typical dynamic fluctuations of the industrial processes and global optimization to increase the production performance while reducing the environmental impact.

SHAREBOX: this project will develop new analysis and optimisation tools for flexible energy use and material flow integration for optimising symbiosis among companies; the platform allows the flexible management of shared process resources that will provide the robust and reliable information needed in real-time to effectively and confidently share resources.

5.4 LITERATURE REVIEW - STATISTICS AND SUMMARY (EUROPEAN + INTERNATIONAL)

In the following section we provide a statistical summary of the literature review for each of the 8 SPIRE sectors considered in the AI-CUBE project (cement, ceramics, chemicals, engineering, minerals, non-ferrous metals, steel and water). This corresponds to the detailed literature review which is documented in Annex 9.1, and the overall summary presented in Section 6.2. Within each sector, each process is evaluated in turn: Market trends and open innovation, Product design, Predictive maintenance, Supply chain management (re) configuring and scheduling, (Model predictive) process control and optimization, Research and innovation management, planning and design.

Note that the literature search in this Section is not limited to only European references, and includes numerous papers from all around the world, where the United States and China are particularly active. We state that this is a true reflection of the real situation, as academic repository and database searches based mainly on technology, process and sector keywords retrieve these results. Also, many publications have co-authors with affiliations from multiple countries around the globe, hence it is difficult to categorize the publications based on geographical region. In other sections EU projects, roadmaps and activity are considered exclusively. In the following subsection 5.5 we provide a summary and comparison of EU projects vs International (non EU).

Firstly, in Figures 4 to 7 can be seen a summary of the number of literature references of AI and BD technologies found by sector, process and technology, for the period 2016-2020. From the trends, a future trend can be extrapolated for future growth in each sector, process and technology, and those which are performing the most and least can also be clearly identified. We note that this literature search is not limited to only European references, and includes numerous papers from all around the world, the United States and China are particularly active.

In Figure 4, showing the summaries by sector, it can be seen that Engineering, Minerals and Steel have the most references, and cement/non-ferrous metals, the least. Ascending trends can be seen for Engineering, Minerals to a lesser degree, Chemicals, Ceramics and Water, taking into to consideration that 2020 is still ongoing at the time of collating these statistics so it would be estimated that the current year's totals will increment at close of year. In Figure 5, which shows the summaries by process, it can be seen that Process Control and Optimization is the clear leader, with an ascendent trend. Product Design and Supply Chain show consistent activity, followed by Predictive Maintenance. Figure 6 shows the summary by AI Technology, where Machine Learning can be seen as the clear leader, followed by Cyber-Physical Systems, Object and Spatial Recognition and Expert Systems. Finally, Figure 7 shows the summary by BD Technology, where Data Management and Data Processing are the leading areas, followed by Computing and Storage Infrastructure. Data Protection has very few references, which may be a consequence of search bias and/or a need for more specific keywords. However, it is expected that as control systems become more dependent on the cloud and wireless data transmission, Data Protection/Cyber Security will become a key issue in the future.

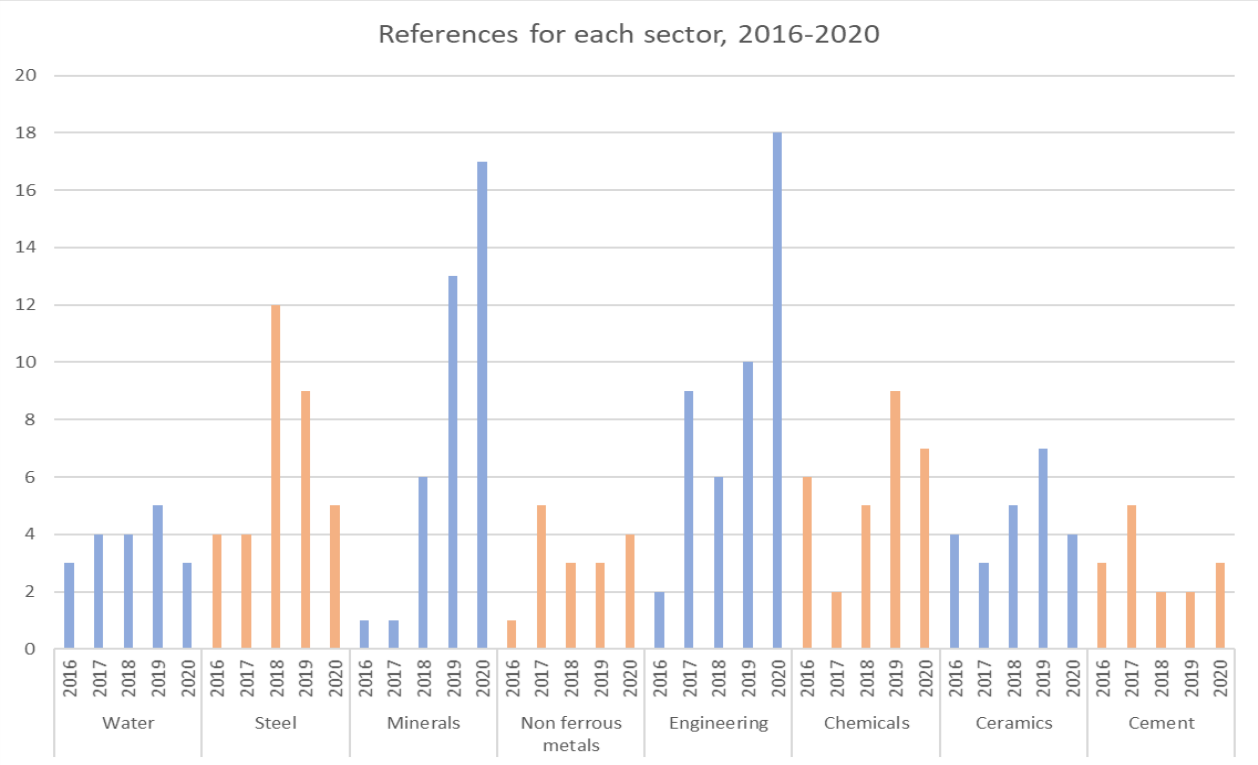

Figure 4. AI and BD literature references found per sector: 2016-2020

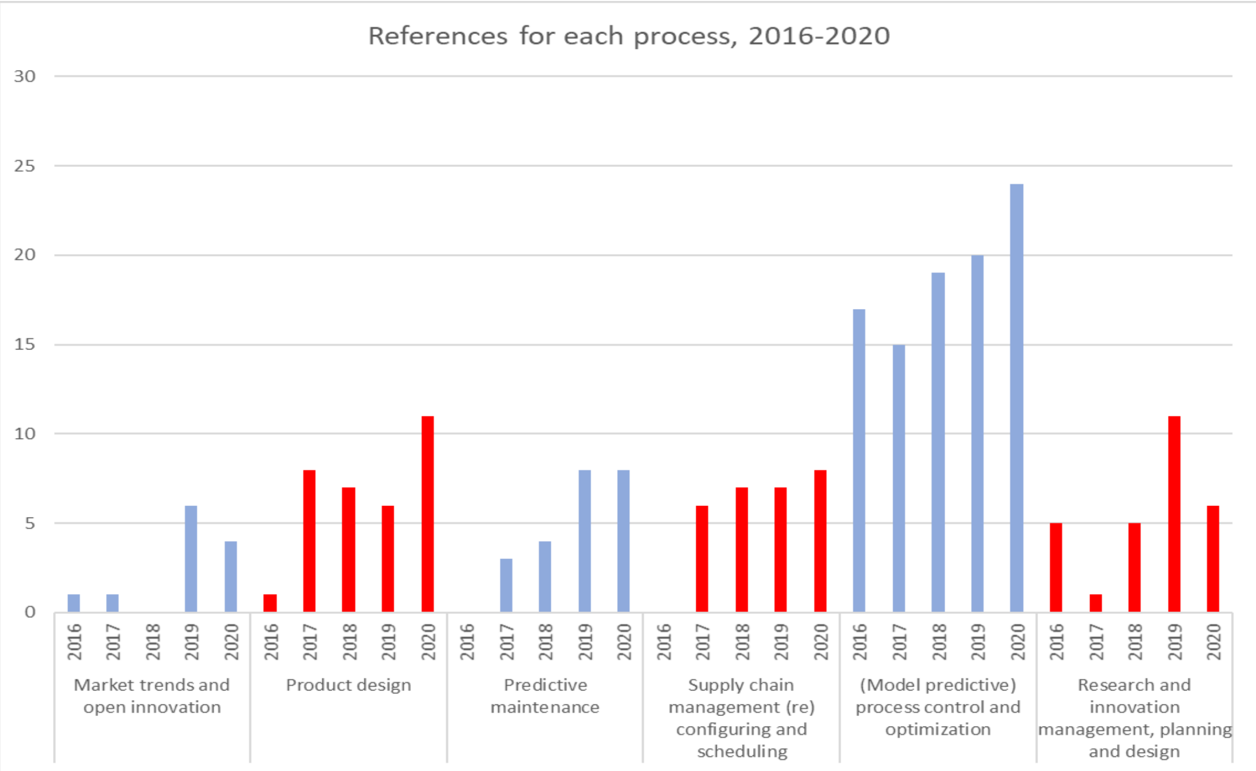

Figure 5. AI and BD literature references found per process: 2016-2020

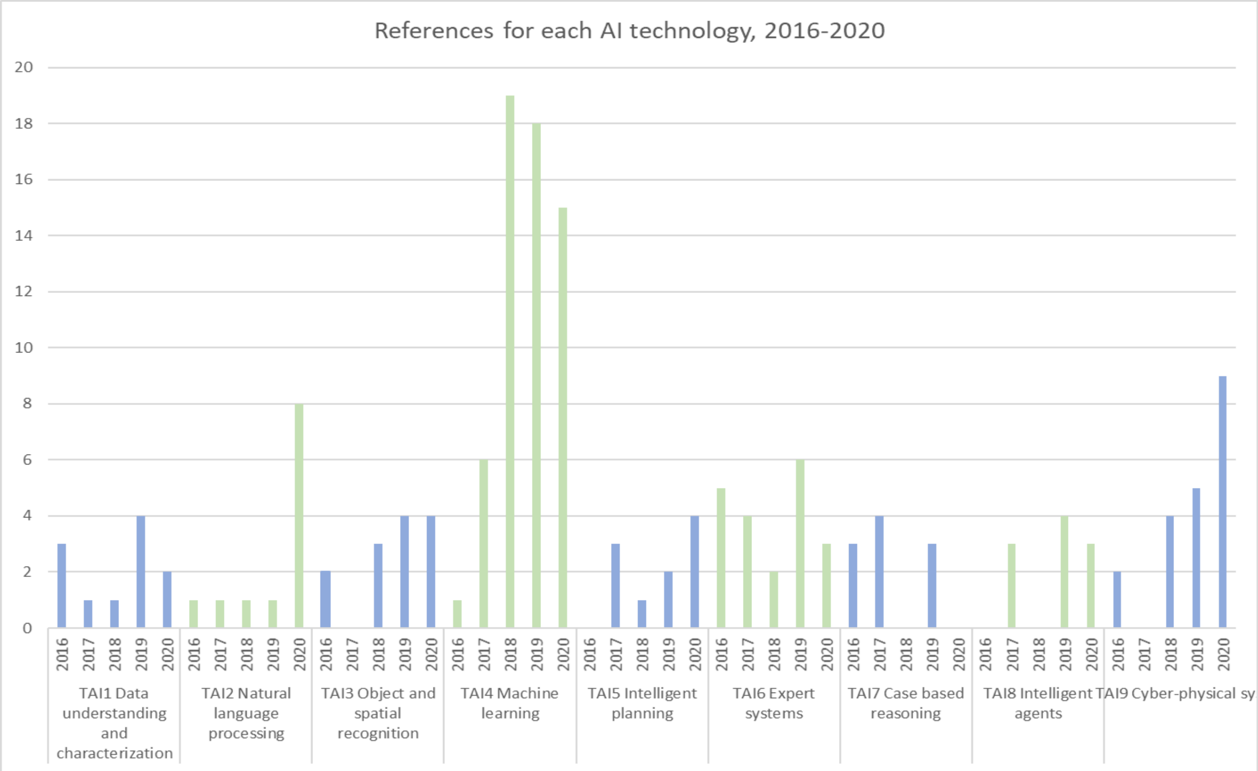

Figure 6. Literature references found per AI technology: 2016-2020

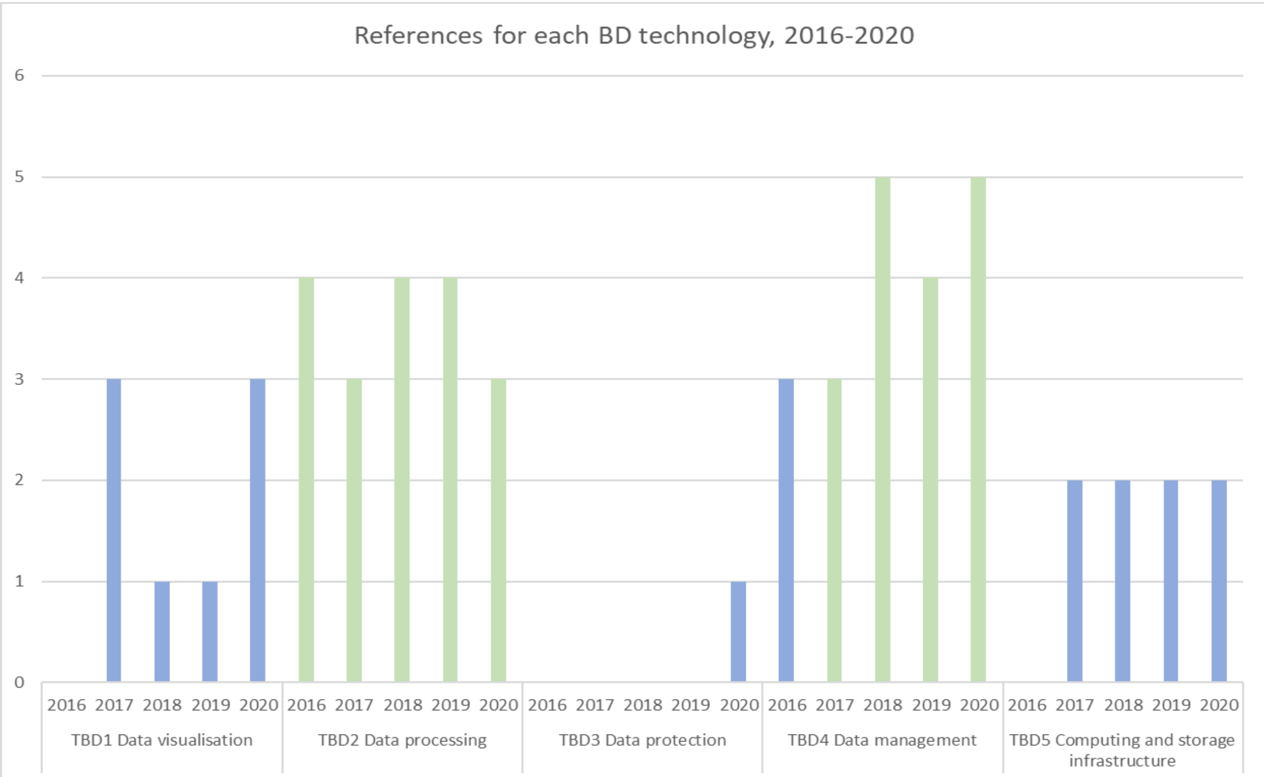

Figure 7. Literature references found per BD technology: 2016-2020

Figures 8 to 10 show “heat maps” for sectors vs processes, sectors vs technologies and processes vs technologies, respectively. The cells indicated in red represent the highest number of references and the green zones represent the lowest. In Figure 7 (sectors vs processes) it can be seen that Process Control is the hottest process (vertically), whereas Engineering and Minerals are the hottest sectors (horizontally). In Figure 9 (Sector vs Technology) it can be seen that Machine Learning is the “hottest” technology (vertically), whereas Engineering is the hottest process (horizontally), with a mention for the Steel sector with a hotspot for Expert Systems. Figure 10 (Process vs Technology) illustrates that the Machine Learning technology is the hottest technology (vertically), whereas Process Control is the hottest process (horizontally), with a mention for Data Management as technology and Supply Chain as process.

	Market trends and open innovation	Product design	Predictive maintenance	Supply chain management (re) configuring and scheduling	(Model predictive) process control and optimization	Research and innovation management, planning and design
Cement	0	3	0	1	7	0
Ceramics	0	2	0	2	9	2
Chemicals	2	0	0	2	7	4
Engineering	4	7	6	7	6	3
Minerals	3	1	3	3	9	5
Non ferrous metals	0	3	0	1	4	2
Steel	0	5	4	4	5	0
Water	0	0	0	2	7	3

HEAT MAP	
>4	high
3-4	medium
0-2	low

Figure 8. Sectors vs Processes: Heat Map for AI/BD references: 2016-2020

	Data understanding and characterization	Natural language processing	Object and spatial recognition	Machine learning	Intelligent planning	Expert systems	Case based reasoning	Intelligent agents	Cyber-physical systems	Data visualization	Data processing	Data protection	Data manage-ment	Computing and storage infrastructure
Cement	0	0	0	2	0	2	1	0	1	2	2	0	1	0
Ceramics	0	0	1	2	1	1	1	1	2	1	3	0	2	0
Chemicals	3	0	1	4	0	0	1	0	1	0	1	0	2	2
Engineering	1	4	0	5	1	3	3	3	3	1	0	1	5	3
Minerals	1	1	2	5	3	1	1	2	1	1	1	1	3	1
Non ferrous metals	0	0	0	3	0	1	1	0	1	1	2	0	1	0
Steel	0	1	1	3	0	4	1	1	3	0	1	0	2	0
Water	0	1	1	3	1	0	0	1	1	2	1	0	1	0

HEAT MAP	
>3	high
2-3	medium
0-1	low

Figure 9. Sectors vs Technologies: Heat Map for AI/BD references: 2016-2020

	Data understanding and characterization	Natural language processing	Object and spatial recognition	Machine learning	Intelligent planning	Expert systems	Case based reasoning	Intelligen t agents	Cyber-physical systems	Data visualization	Data processing	Data protection	Data manage-ment	Computing and storage infrastructure
(Model predictive) process control and optimization	1	1	5	7	3	5	5	1	7	4	7	0	6	2
Market trends and open innovation	1	2	0	3	0	0	0	1	0	0	0	0	1	1
Predictive maintenance	0	1	1	2	0	2	2	1	2	0	0	0	1	1
Product design	0	2	1	6	0	3	1	0	1	2	2	0	3	0
Research and innovation management, planning and design	3	0	0	5	1	0	0	1	0	1	2	1	4	1
Supply chain management (re) configuring and scheduling	0	1	0	4	2	2	1	4	3	1	0	1	2	1

HEAT MAP

>4	high
3-4	medium
0-2	low

Figure 10. Process vs Technologies: Heat Map for AI/BD references: 2016-2020

Figures 11 and 12 shows “Tre-Maps for Sectors vs Processes and Sectors vs Technologies, respectively. Note that the categories of processes, technologies and sectors are the same ones as described previously (Section 4, Table 1). The Tre-Maps are hierarchical maps which show the sectors as different coloured rectangles and inside them, smaller sub-rectangles represent the processes. The size of the rectangles is proportional to the number of references and thus their relative importance. In this way, in Figure 11 it is easy to see that Engineering and Minerals are the biggest sectors and within Minerals, Process Control is the biggest process. In Figure 12, again it can be seen that Engineering and Minerals are the biggest sectors and within Minerals, Machine Learning is the biggest technology; also, within Engineering, Natural Language Processing and Cyber-Physical Systems are the biggest technologies.

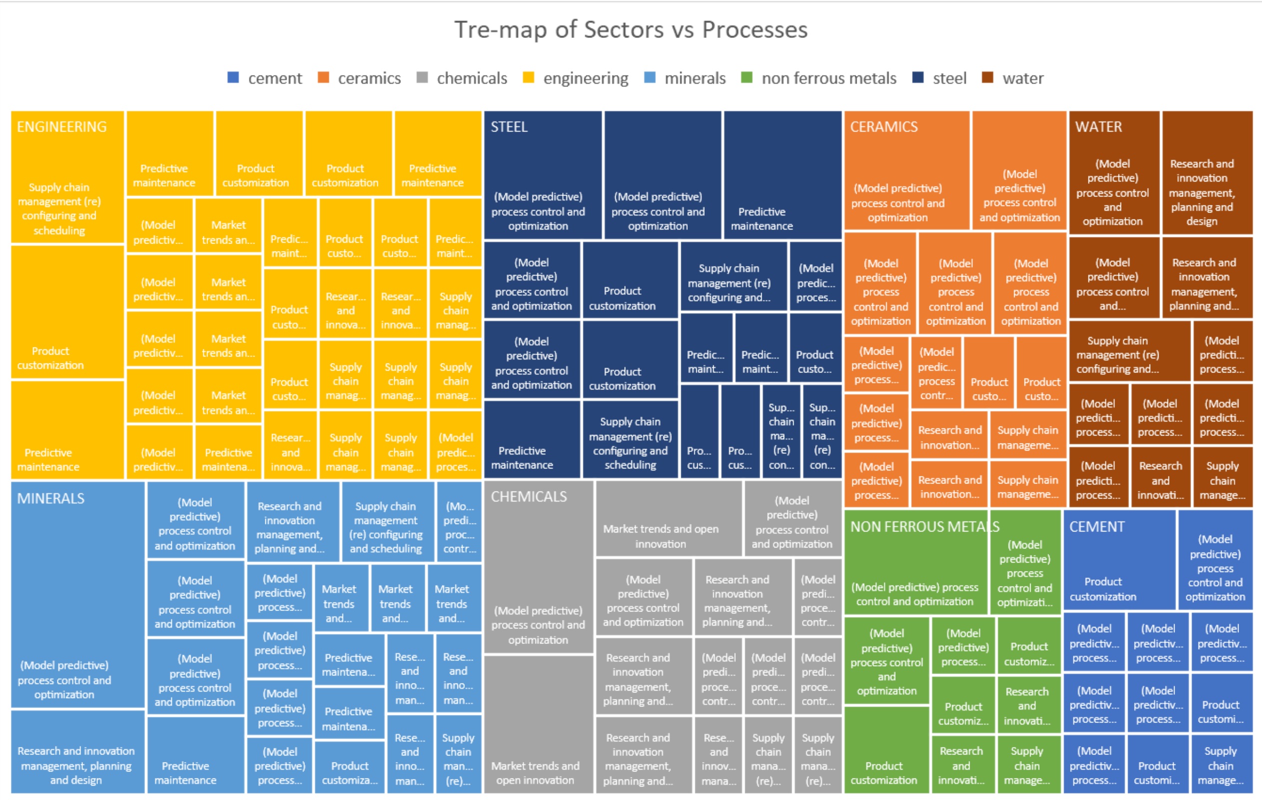

Figure 11. Tre-Map of Sectors vs Processes

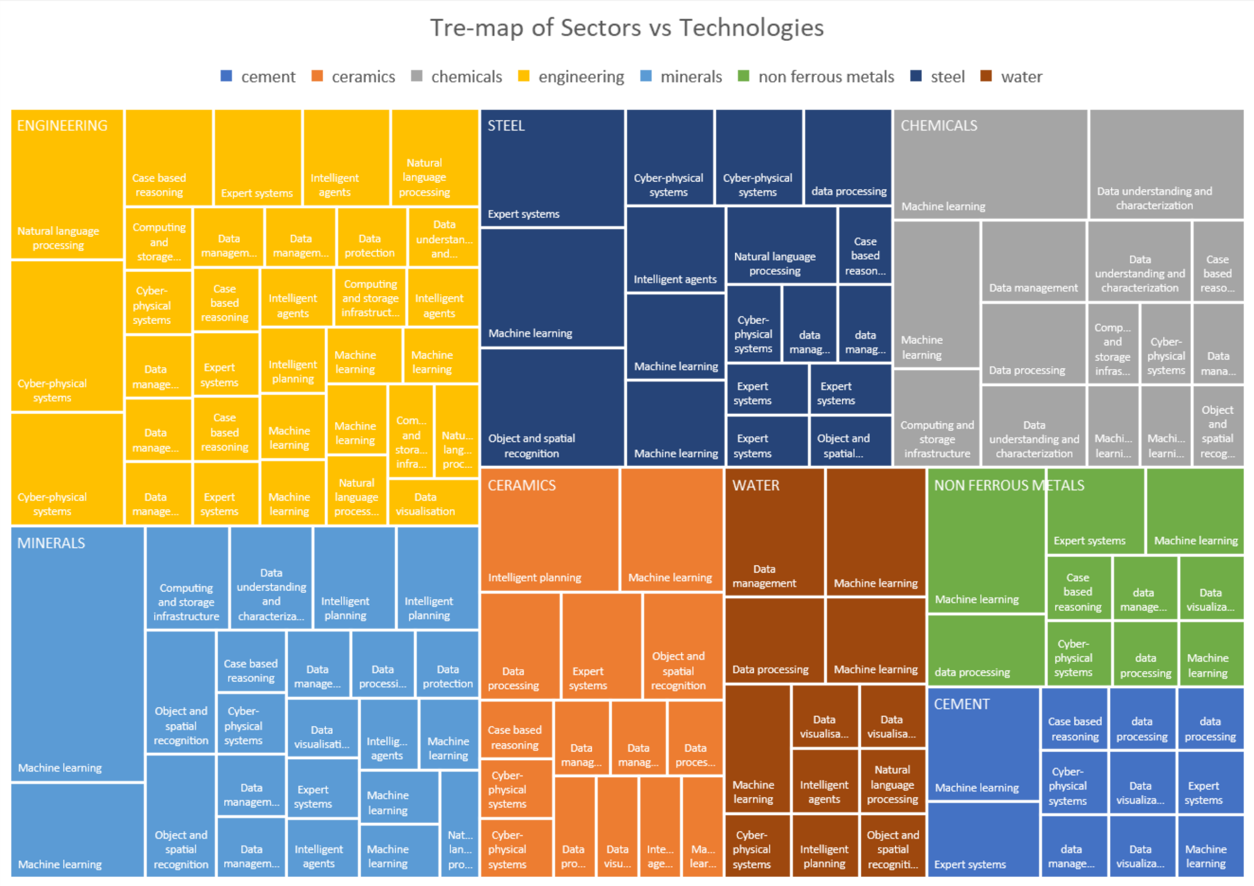

Figure 12. Tre-Map of Sectors vs Technologies

5.5 EUROPEAN VS INTERNATIONAL (NON EU) REFERENCES

In general, it can be seen that technologies are pan-border and similar technologies, similar algorithms and techniques are used in the EU region, China, US and other countries.

However, it can be seen that the volume of publications can vary by sector depending on geographical region. We note that the geographic region is taken from the affiliations of the authors of the paper, in each case. If there are a mixture of different countries, a "simple majority" decides the overall geographical region. Note that it is often seen that the nationalities of the authors (as taken from their names) is different from their affiliation (location of their university/company).

For all the references in Section 5.4 /Section 8, we have identified the "nationality" of the articles, using the process just mentioned. The following tables give a summary of the frequencies by EU vs Non-EU and by individual country. In Table 4 it can be seen that in general the non EU countries have a higher share (about 2:1) with some notable exceptions. The top sectors for EU share are Water, Non-Ferrous and Engineering bd with 54%, 50% and 46% share respectively. On the other hand the top sectors for non-EU are Cement, Minerals and Engineering-AI with 95%, 79% and 77% share respectively. The search criteria used keywords based on technology, sector and process so should be “country-agnostic”, however, depending on the database, information search tool, biases could be introduced. It is curious the very high bias in the cement sector.

Table 4 Summary of publication frequencies by sector and EU vs non EU

SECTOR	EU		NON EU		TOTAL
	#	%	#	%	#
STEEL	12	0.34	23	0.66	35
MINERALS	8	0.21	31	0.79	39
NONFERROUS	11	0.5	11	0.5	22
ENGINEERING-AI	13	0.23	43	0.77	56
ENGINEERING-BD	6	0.46	7	0.54	13
WATER	20	0.54	17	0.46	37
CHEMICAL	17	0.44	22	0.56	39
CERAMICS	12	0.34	23	0.66	35
CEMENT	1	0.05	21	0.95	22
ALL SECTORS	100	0.34	198	0.66	298

Table 5 shows the ranking by country of publication frequency for all sectors. The top 10 countries are shown, and it is clear that the main weighting is given by China and the USA. The four EU countries which appear in the top 10 are Italy, UK, Germany and Spain, in that order. It is curious the lack of publications by Japan.

Table 5 Summary of publication frequencies by country for all sectors

CHINA	42
USA	30
ITALY	15
TAIWAN	14
UK	13
BRAZIL	12
GERMANY	12
AUSTRALIA	12
INDIA	10
SPAIN	10

With respect to technologies, we reviewed specific sectors (engineering-AI and chemical, among others) to evaluate if there were differences in the frequency of specific technologies, in terms of geographical region. Overall, the focus areas in terms of technologies and processes were found to be fairly similar.

In the case of Engineering-AI (International), cited technologies included agents, language processing, experts systems and cyber-physical systems, and cited processes included predictive maintenance, supply chain and value chain. On the other hand, Engineering-AI (European) included technologies such as cyber-physical and agents, and processes such as predictive maintenance and supply chain.

In the case of Chemical (International), cited technologies included machine learning, data analytics, cyber-physical, data analytics and data processing, and processes such as fault diagnosis, process modelling, sensor maintenance and process optimization. On the other hand, Chemical (European) included technologies such as decision support, data preprocessing, big sensor data, deep learning and cyber-physical, and processes such as product innovation, process optimization, process control, predictive maintenance and green process optimization.

6. Synthesis and Evaluation

In the following sections we perform a synthesis of the previous literature review and inventory of roadmaps and running projects, in order to obtain an overall picture of the current situation, identifying strong and weak points, and with a prevision to future evolution. This covers the roadmap and projects search (6.1), and the literature review summary together with a set of overall commentaries and observations on technology key features, maturity level and applicability (6.2).

6.1 SUMMARY OF EUROPEAN ROADMAPS AND PROJECTS

The following gives an overall summary of the search for roadmaps and running projects described in Section 5.2.

With respect to scientific and technological roadmaps at a European level (Section 5.2.1), their analysis has highlighted that the different sectors have recognised the importance of the AI and BD technologies and that research actions for their further development are needed. Even though each roadmap has its own peculiarities and goals, there are some common topics, such as the need for improving the interaction between intelligent systems and humans and the external environment, or the implementation of AI for the monitoring and optimization of parameters.

With respect to political initiatives at European, country and regional Level (Section 5.2.2), to summarize the national plans, it can be seen that common elements exist, as they are in general aligned with the overall EU strategy for AI. Aspects such as education and training of new talent, ethics for AI use, and job creation (ask there is also the risk of people losing jobs due to automation of certain skills/tasks). All of these aspects are relevant for the SPIRE process industries.

Thirdly, with respect to the mapping of running projects (Section 5.2.3), Table 6 shows how frequently the technological keywords are used in the description or in the title of the projects. The most common are “big data” and “artificial intelligence” and often these keywords are employed with others. It is observed that for the SPIRE projects the most used keyword is “cognition” and/or “reasoning”, while only four projects refer directly to “big data” and “artificial intelligence”; moreover, “storage infrastructure”, “business analytics”, “natural processing language” and “computer infrastructure”, are the four least or unused keywords. In addition, in the ICT projects, the most used list is the one related to the BD technologies, while for SPIRE and FoF the most frequent keywords are linked to the AI technologies.

If we compare the search results (based on technology category) of Table 6 (European) with Figs. 6 and 7 (European + International) it can be seen that “machine learning” has a high ranking in both. However, due to different (more generic) categories in Table 6 (such as AI and big data), the results are not directly comparable. However, it can be seen that several of the most frequent categories of Figs. 6 and 7 (machine learning, cyber-physical systems, data management) also appear in the higher positions in Table 6. Also, the generic categories of AI, “real-time”, “cognition/reasoning” and “big data analytics/analysis” could be matched in Figs. 6 and 7 with the more specific categories of “object and spatial recognition”, “data processing” and “data visualization”.

Table 6 Frequencies of Technology keywords for different European project call types

Keyword	*Total*	ICT	FOF	SPIRE
big data	111	105	4	2
artificial intelligence	92	82	8	2
machine learning	40	34	4	2
real time	39	30	6	3
big data analytics/analysis	30	29	1	0
data management	29	25	3	1
cognition/reasoning	41	30	5	6
deep learning	12	12	0	0
cyberphysical systems	14	10	4	0
distributed ledger	9	7	2	0
storage infrastructure	2	1	1	0
business analytics	1	1	0	0
natural language processing	1	1	0	0
computer infrastructure	0	0	0	0

In Figure 13, the assignment of the projects to the 6 macro-areas process shows that there are similarities between ICT, SPIRE and FoF: in each call most of the effort has been dedicated to the development of applications for process control and optimization whereas fewer projects focus on predictive maintenance, product customization and supply chain. No reference has been found for market trend and open innovation, and research and innovation management.

If we compare the process results of Fig. 13 (European) with Fig. 6 (European + International) it can be seen that in general they are quite similar, the most frequent process being “process control and optimization”. However, for the European zone, “predictive maintenance” and “supply chain” are the second and third most frequent processes (in that order), whereas internationally, “product design” and “supply chain” are second and third respectively. The lack of EU references for “research and innovation” is due to the search keywords in the EU project database which were unable to find that category.

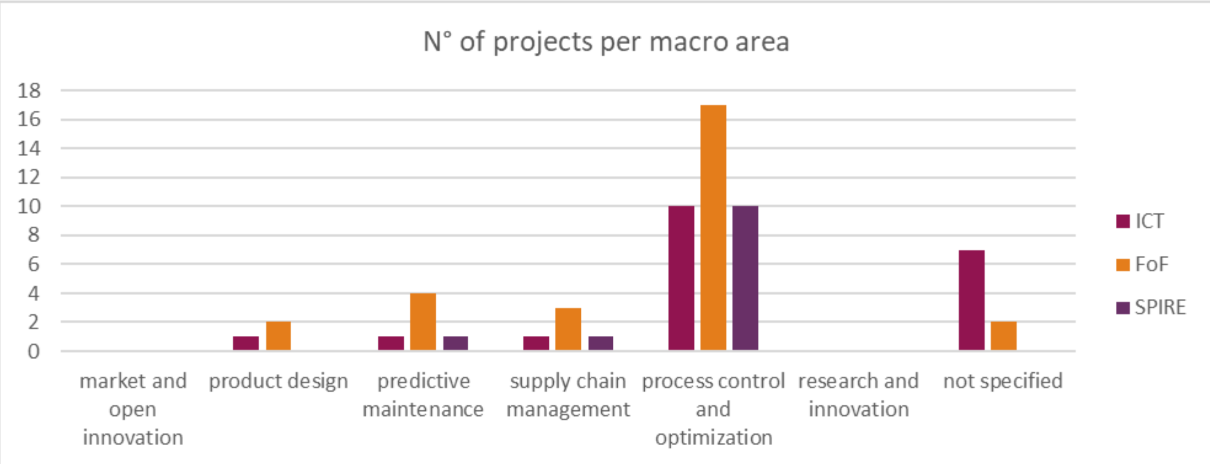

Figure 13. Number of European projects vs process macro-area

To summarize, the key technological areas and processing identified in the roadmaps and projects, coincide in general with the literature search results, as would be expected.

6.2 TECHNOLOGY KEY FEATURES, MATURITY LEVEL AND APPLICABILITY

From the literature reviews (Sections 5.3 and 9.1), ongoing projects and roadmaps (5.2) we are able to obtain a general overview of the main processes in which the AI and BD technologies are applied in the process industry.

Overall, it is clear that some technologies are more applicable to process sector industries than others, and some processes are more applicable for AI and BD technologies. One key area where a scarcity of material was evident, Data privacy/cyber security, raises a flag for these industries to focus more on this area in the future. In general, process control is a favourite process for AI and BD as is to be expected by the large amounts of data generated by sensor data capture in-line. However, there are many "off-line studies using data captured historically and there is still difficulty in making the leap from off-line studies to on-line deployment. Embedding a trained machine learnt model in a run-time system is still a tricky step and one possible cause is the lack of data scientists and IT support who are sufficiently trained in embedding runtime systems deployment. Hence one recommendation, following the AI roadmap plan guidelines for Europe and individual countries, is to have a medium/long term plan for training a new generation of data scientists with skills for deploying such systems. Also, making available the software and hardware infrastructures necessary for successful deployment.

On the other hand, adequate software tools already exist for deploying big data management systems, and in the field of artificial vision, smart sensor technology and cyber-physical systems (esp. autonomous robotics, human-robot collaboration, etc.), AI is being successfully deployed "close to the edge" in the factory floor.

In the **"water" sector**, the search of the AI&BD technologies revealed a scarcity of references in the application of AI&BD technologies in the "market trends and open innovation", "product customization", and "predictive maintenance" areas. For the "**non-ferrous metals**" sector, the references were focused mainly on copper and aluminium, as they are two of the most known non-ferrous metals. In the **"steel"** sector, a concentration of references was found related to the development of machine learning tools and to data processing solutions is about 500; on the other hand, relatively few references were found related to "Natural Language Processing" or "Expert Systems". This is a first indication related to the possible existing gaps that should be covered by future research in order to apply AI and BD technologies more widely, especially in the steel sector which represents one of the most important industries for the European economy.

The most advanced sectors were found to be "engineering", "chemicals" and "minerals", whereas the most traditional sectors were found to be "ceramics", "cement" and "non-ferrous metals.

The trends over the last five years (2016-2020) show exponential growth in some areas:

- Sectors: Engineering, Minerals
- Processes: Process control (predictive models)
- Technologies: Machine learning, Cyber-physical systems

In a nutshell we could say that, based on the literature searches, and looking at trends in other sectors, it may be expected that the following developments are likely to occur in the upcoming period:

- The deployment as the "end-game" for AI projects, especially for processes such as process control and predictive maintenance, and technologies such as machine learning, data models.
- Greater use of AI and BD in predictive maintenance.
- Greater use of AI in processes such as marketing, supply chain and planning, product design.
- Modernization of "traditional" sectors such as ceramics, cement and non-ferrous metals. Emphasis on training (academic and on-the-job) for a future generation of data scientists, applied AI and DB specialists.

6.2.1. TRL perspective in European projects

Based on the EU projects (ICT, FOF, SPIRE) analysed in 5.2.3. we have further investigated the TRL of the AI/BD technologies. Taking into consideration the full list of projects extracted from the CORDIS database, all the FOF and SPIRE projects have been considered in this analysis because they are all industrial driven projects, in ICT call only projects with direct application to industry have been retained for this purpose without considering projects that are purely linked to ICT development. At this stage, the technologies have been categorised according to the taxonomy defined in AI-CUBE and for each project, the TRL ranges considered are the following three categories:

- TRL 2-5
- TRL 4-6
- TRL 5-7

For the calls where the TRL was explicitly mentioned we assigned it to the projects, for calls where the TRL was not indicated, we decided to approximate it based on the typology of project and typology of call, i.e. in case of RIA projects in ICT it was 2-5, in FOF and SPIRE TRL4-6; in the case of IA projects in ICT calls it was approximated to TRL4-6 and in FOF and SPIRE projects, TRL 5-7.

The assignment of the AI/BD technology to each project is based on the text of the call and the abstract of each project, with each project possibly covering more than one technology.

Table 7 depicts the TRL levels taking into consideration calls and AI/BD technologies. While ICT projects are more focused on projects with lower TRL, FOF and SPIRE are generally more applicative with a larger amount of projects with a higher TRL.

	ICT	TRL2-5	TRL4-6	TRL5-7	FOF	TRL2-5	TRL4-6	TRL5-7	SPIRE	TRL2-5	TRL4-6	TRL5-7
Data understanding and characterization	6	3	3		2			2	1	1		
Natural language processing	2	1	1		2		1	1	0			
Object and spatial recognition	3	3			2		2		1			1
Machine learning	7	5	2		4		2	2	6		1	5
Intelligent planning	4	2	2		1			1	1			1
Expert systems	2	1	1		1			1	1			1
Case based reasoning	3	2	1		5		1	4	2			2
Intelligent agents	4	1	3		2			2	0			
Cyber-physical systems	2	2			4		3	1	1			1
Data visualization	1	1			4		2	2	1		1	
data processing	2	2			5		3	2	3	1		2
data protection	3	1	2		2			2	0			
data management	4	1	3		3		1	2	1		1	
Computing and storage Infrastructures	0				2			2	0			
	43	25	18	0	39	0	15	24	18	2	3	13

Table 7: TRL level per technology per call type

The three typologies of projects summarized together in a heatmap as seen below in Table 8, highlights two things: the prevalence of projects focussed on machine learning and the high range of TRL for most of the projects.

	TRL2-5	TRL4-6	TRL5-7
Data understanding and characterization	4	3	2
Natural language processing	1	2	1
Object and spatial recognition	3	2	1
Machine learning	5	5	7
Intelligent planning	2		2
Expert systems	1		3
Case based reasoning	2	2	5
Intelligent agents	1	3	2
Cyber-physical systems	2	3	2
Data visualization			
data processing	3	3	4
data protection			
data management	1	5	2
Computing and storage Infrastructures	0	0	3
	25	28	34
		<2	low
		3-4	medium
		>5	high

Table 8: heatmap of European projects' TRL

7. CONCLUSIONS

The objective of this document has been to obtain a snapshot of the current landscape of AI & BD technologies and industry applications for the SPIRE process sectors. This has been done by first defining the terminology for AI and BD, tailored for process industries, via the elaboration of taxonomies. Next, we have reviewed European roadmaps from process industry, ICT and manufacturing sectors to underline the most important topics related to AI and BD technologies, and listed the most important political initiatives at European and national levels. This has been complemented by a detailed systematic search for each sector, of recent publications dealing with AI and DB applied to the given sector. This has facilitated the identification of how AI and BD are being applied in each industry, with real use cases. In a similar manner, a recompilation of running EC projects has been elaborated, thus identifying technologies and applications developed in ICT, FoF and SPIRE calls. From the recompilation of publications, a summary has been produced for each sector.

From the graphics which summarize the state-of-the-art search, the increasing number of references over time can be seen by sector, process and technology, during the period 2016 through to 2020. This allows us to extrapolate the trend for each of these dimensions of the AI-CUBE, for the coming years (e.g., next 5 years). It identifies the sectors which are experiencing strongest AI/BD activity, such as chemicals and engineering; processes, such as predictive maintenance and process control; and technologies such as machine learning, computer vision and data processing/management.

At this early stage of the project, we have not yet entered into the dynamics of stakeholder participation and input, however we expect this to enrich the content of the upcoming deliverables in the remainder of WP1, WP2, etc.

The next steps envisaged once completed deliverable D1.1 are as follows: (**a**) development work on Task 1.2 will complement the basis defined in Task 1.1; (**b**) Preparation for the first stakeholder workshop planned for the beginning of February 2021; (**c**) use of D1.1 to provide input for WP2.

8. BIBLIOGRAPHY / REFERENCES

AI TAXONOMIES

1. European Commission report (2020): "AI Watch Defining Artificial Intelligence -Towards an operational definition and taxonomy of artificial intelligence. Report by the Joint Research Centre (JRC), the European Commission's science and knowledge service.
2. https://www.sciencedirect.com/topics/physics-and-astronomy/artificial-intelligence
3. https://www.forbes.com/sites/cognitiveworld/2018/08/22/ai-knowledge-map-how-to-classify-ai-technologies/#3568a0907773
4. https://www.researchgate.net/figure/A-taxonomy-of-some-of-the-best-known-artificial-intelligence-methods_fig9_325162420
5. https://itpeernetwork.intel.com/artificial-intelligence-technology-the-path-forward/#gs.ip9d95

BIG DATA TAXONOMIES

6. https://downloads.cloudsecurityalliance.org/initiatives/bdwg/Big_Data_Taxonomy.pdf
7. https://www.researchgate.net/figure/Taxonomy-of-Big-Data-and-Analytics-Solutions-for-IoT-Systems_fig1_317617290
8. https://www.researchgate.net/figure/An-integrated-Big-Data-system-in-the-process-industry_fig1_320756173
9. https://research.engineering.uiowa.edu/kusiak/sites/research.engineering.uiowa.edu.kusiak/files/files/Data-drivenSmartManufacturing.pdf
10. https://research.engineering.uiowa.edu/kusiak/sites/research.engineering.uiowa.edu.kusiak/files/files/Data-drivenSmartManufacturing.pdf
11. https://www.sciencedirect.com/science/article/pii/S2215098618317750

ROADMAPS

12. European Commission WHITE PAPER Feb. 2020 On Artificial Intelligence - A European approach to excellence and trust
13. AI Watch - Monitor the development, uptake and impact of Artificial Intelligence for Europe. https://ec.europa.eu/knowledge4policy/ai-watch_en
14. France AI Strategy (2018)
15. Italy - National Strategy on Artificial Intelligence (august 2019)
16. Germany - artificial intelligence strategy
17. Spain: Pedro Sánchez presenta la Estrategia Nacional de Inteligencia Artificial. La Moncloa, Madrid, miércoles 2 de diciembre de 2020. https://www.lamoncloa.gob.es/multimedia/videos/presidente/Paginas/2020/021220-estrategia-ia.aspx?fbclid=IwAR2iEr367HkKYEUjTrsY_B9p-MmHPh9ZxAUgeh9zsFjhkgYrymUnzCC_fNU
18. SPIRE ROADMAP - Sustainable Process Industry through Resource and Energy Efficiency. Pablo Tello, Ron Weerdmeester, PNO Consultants.
19. https://www.spire2030.eu/sites/default/files/pressoffice/spire-roadmap.pdf
20. EFFRA 2019: VISION FOR A MANUFACTURING PARTNERSHIP IN HORIZON EUROPE
21. SPIRE document "Process4Planet roadmap", draft published in June 2020. https://ec.europa.eu/info/sites/info/files/research_and_innovation/funding/documents/ec_rtd_he-partnerships-industry-for-sustainable-society.pdf

STEEL SECTOR

22. Ananthapadmanaban, D., & Karthik, A. (2019). Development of an Expert System to Monitor Casting Defects in Foundries. In Advances in Manufacturing Processes (pp. 101-109). Springer, Singapore.
23. Beskardes, A., Hames, Y., Cevik, S., Kaya, K., & Ozdemir, E. (2019, September). Fuzzy Logic Based Sinter RDI Optimization. In 2019 4th International Conference on Power Electronics and their Applications (ICPEA) (pp. 1-4). Ieee.
24. "Bettinger D., Fritschek H., Kronberger T., Mauhart J., Schaler M.,""Risk and knowledge management with blast furnace process optimization systems"",2018,
25. Spirin, N. A., Shvidkii, V. S., Yaroshenko, Y. G., & Lavrov, V. V. (2018, October). Mathematical modelling of ladle furnace thermal regime with bubble melt blowing by gas. In IOP Conference Series: Materials Science and Engineering (Vol. 411, No. 1, p. 012074). Institute of Physics Publishing."
26. Boral, S., Chaturvedi, S. K., & Naikan, V. N. A. (2019). A case-based reasoning system for fault detection and isolation: a case study on complex gearboxes. Journal of Quality in Maintenance Engineering.
27. Byeong-Woo, J., Dae-Geun, H., Kee-Young, S., & Suk-Hwan, S. (2016, July). Conceptual Framework of Smart Manufacturing Execution System Based on Systems Engineering Approach. In INCOSE International Symposium (Vol. 26, No. 1, pp. 2118-2133).
28. Chenhao, Z., & Chengyao, W. (2019, October). Named entity recognition in steel field based on BiLSTM-CRF model. In Journal of Physics: Conference Series (Vol. 1314, No. 1, p. 012217). IOP Publishing.
29. Costoiu, M., Ioana, A., Semenescu, A., & Marcu, D. (2016, November). EAF management optimization. In ISI Proceedings of “20th Innovative Manufacturing Engineering and Energy Conference (ImanEE 2016) (Vol. 161, pp. 23-25).
30. Duarte, I. C. D., Almeida, G. M. D., & Cardoso, M. (2020). Heat-loss cycle prediction in steelmaking plants through artificial neural network. Journal of the Operational Research Society, 1-12.
31. Fumagalli, L., Cattaneo, L., Roda, I., Macchi, M., & Rondi, M. (2019). Data-driven CBM tool for risk-informed decision-making in an electric arc furnace. The International Journal of Advanced Manufacturing Technology, 105(1-4), 595-608.
32. Han, Y., Zhang, C. J., Wang, L., & Zhang, Y. C. (2019). Industrial IoT for Intelligent Steelmaking With Converter Mouth Flame Spectrum Information Processed by Deep Learning. IEEE Transactions on Industrial Informatics, 16(4), 2640-2650.
33. Hatterscheid, E., & Schlüter, F. (2018, April). Towards a decision support approach for selecting physical objects in collaborative supply chain processes for cyber physical system-transformation. In 2018 5th International Conference on Industrial Engineering and Applications (ICIEA) (pp. 1-5). IEEE.
34. Hu, W., Gu, F., & Chen, S. (2020). Large Data and AI Analysis Based Online Diagnosis System Application of Steel Ladle Slewing Bearing. In Advances in Asset Management and Condition Monitoring (pp. 1519-1527). Springer, Cham.
35. Kang, L. W., Chen, Y. T., Jhong, W. C., & Hsu, C. Y. (2018, November). Deep learning-based identification of steel products. In International Conference on Intelligent Information Hiding and Multimedia Signal Processing (pp. 315-323). Springer, Cham.
36. Kang, L. W., Chen, Y. T., Jhong, W. C., & Hsu, C. Y. (2018, November). Deep learning-based identification of steel products. In International Conference on Intelligent Information Hiding and Multimedia Signal Processing (pp. 315-323). Springer, Cham.

37. Karagiorgou, S., Vafeiadis, G., Ntalaperas, D., Lykousas, N., Vergeti, D., & Alexandrou, D. (2019, May). Unveiling Trends and Predictions in Digital Factories. In 2019 15th International Conference on Distributed Computing in Sensor Systems (DCOSS) (pp. 326-332). IEEE.
38. Kim, D., Han, S. C., Lin, Y., Kang, B. H., & Lee, S. (2018). RDR-based knowledge based system to the failure detection in industrial cyber physical systems. Knowledge-Based Systems, 150, 1-13.
39. Kim, D., Han, S. C., Lin, Y., Kang, B. H., & Lee, S. (2018). RDR-based knowledge based system to the failure detection in industrial cyber physical systems. Knowledge-Based Systems, 150, 1-13.
40. Klinger A., Altendorfer A., Bettinger D., Hughes G.D., Al-Husseini A.A., Gupta D.R.,"The new system for control and improvement of technological process at DRI units",2017
41. Klinger A., Altendorfer A., Bettinger D., Hughes G.D., Al-Husseini A.A., Gupta D.R.,"The new system for control and improvement of technological process at DRI units",2017
42. Kong, Y., Chen, D., Liu, Q., & Long, M. (2019). A prediction model for internal cracks during slab continuous casting. Metals, 9(5), 587.
43. Lahmadi, A., Terrissa, L., & Zerhouni, N. (2018, March). A data-driven method for estimating the remaining useful life of a composite drill pipe. In 2018 International Conference on Advanced Systems and Electric Technologies (IC_ASET) (pp. 192-195). IEEE.
44. Liu, L. L., Wan, X., Gao, Z., Li, X., & Feng, B. (2019). Research on modelling and optimization of hot rolling scheduling. Journal of Ambient Intelligence and Humanized Computing, 10(3), 1201-1216.
45. Mourtzis, D., Milas, N., Vlachou, K., & Liaromatis, I. (2018, April). Digital transformation of structural steel manufacturing enabled by IoT-based monitoring and knowledge reuse. In 2018 5th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 295-301). IEEE.
46. Pang, X. F., Jiang, Y. C., Gao, L., Tang, B., Li, H. B., Yu, S. P., & Liu, W. (2017, May). Dynamic scheduling system for steelmaking-refining-continuous casting production. In 2017 29th Chinese Control And Decision Conference (CCDC) (pp. 4710-4715). IEEE.
47. Peng, K., Pan, Q. K., Gao, L., Zhang, B., & Pang, X. (2018). An improved artificial bee colony algorithm for real-world hybrid flowshop rescheduling in steelmaking-refining-continuous casting process. Computers & Industrial Engineering, 122, 235-250.
48. Peng, K., Zhang, K., You, B., Dong, J., & Wang, Z. (2016). A quality-based nonlinear fault diagnosis framework focusing on industrial multimode batch processes. IEEE Transactions on Industrial Electronics, 63(4), 2615-2624.
49. Ruiz, E., Ferreño, D., Cuartas, M., López, A., Arroyo, V., & Gutiérrez-Solana, F. (2020). Machine learning algorithms for the prediction of the strength of steel rods: an example of data-driven manufacturing in steelmaking. International Journal of Computer Integrated Manufacturing, 33(9), 880-894.
50. Ruiz-Sarmiento, J. R., Monroy, J., Moreno, F. A., Galindo, C., Bonelo, J. M., & Gonzalez-Jimenez, J. (2020). A predictive model for the maintenance of industrial machinery in the context of industry 4.0. Engineering Applications of Artificial Intelligence, 87, 103289.
51. Tirian, G. O., Filip, I., & Proştean, G. (2014). Adaptive control system for continuous steel casting based on neural networks and fuzzy logic. Neurocomputing, 125, 236-245.
52. Valente, F. J., & Neto, A. C. (2017, September). Intelligent steel inventory tracking with IoT/RFID. In 2017 IEEE International Conference on RFID Technology & Application (RFID-TA) (pp. 158-163). IEEE.
53. Vannocci, M., Colla, V., Pulito, P., Zagaria, M., Di Mastromatteo, V., & Saccone, M. (2014, October). Fuzzy Control of a Sintering Plant. In IJCCI (FCTA) (pp. 68-75).
54. Wang, C., Xu, L. Y., & Fan, J. S. (2020). A general deep learning framework for history-dependent response prediction based on UA-Seq2Seq model. Computer Methods in Applied Mechanics and Engineering, 372, 113357.

55. Xiang, F., Zhi, Z., & Jiang, G. (2018, March). Digital Twins technolgy and its data fusion in iron and steel product life cycle. In 2018 IEEE 15th international conference on networking, sensing and control (ICNSC) (pp. 1-5). IEEE.
56. Zhang, F., Liu, M., Zhou, Z., & Shen, W. (2016). An IoT-based online monitoring system for continuous steel casting. IEEE Internet of Things Journal, 3(6), 1355-1363.
57. Zhang, M., Sun, C. N., Zhang, X., Wei, J., Hardacre, D., & Li, H. (2018). Predictive models for fatigue property of laser powder bed fusion stainless steel 316L. Materials & Design, 145, 42-54.

MINERALS SECTOR

1. Acosta, I. C. C., Khodadadzadeh, M., Tusa, L., Ghamisi, P., & Gloaguen, R. (2019). A machine learning framework for drill-core mineral mapping using hyperspectral and high-resolution mineralogical data fusion. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 12(12), 4829-4842.
2. Ali, D., & Frimpong, S. (2020). Artificial intelligence, machine learning and process automation: existing knowledge frontier and way forward for mining sector. Artificial Intelligence Review, 1-18.
3. Ali, D., Hayat, M. B., Alagha, L., & Molatlhegi, O. K. (2018). An evaluation of machine learning and artificial intelligence models for predicting the flotation behavior of fine high-ash coal. Advanced Powder Technology, 29(12), 3493-3506.
4. Andriamasinoro, F., & Danino-Perraud, R. (2019). Use of artificial intelligence to assess mineral substance criticality in the French market: the example of cobalt. Mineral Economics, 1-19.
5. Barik, R. K., Lenka, R. K., Simha, N. V. R., Dubey, H., & Mankodiya, K. (2017). Fog computing based SDI framework for mineral resources information infrastructure management in india. arXiv preprint arXiv:1712.09282.
6. Boral, S., Chaturvedi, S. K., & Naikan, V. N. A. (2019). A case-based reasoning system for fault detection and isolation: a case study on complex gearboxes. Journal of Quality in Maintenance Engineering.
7. Chen, W., Shahabi, H., Shirzadi, A., Hong, H., Akgun, A., Tian, Y., ... & Li, S. (2019). Novel hybrid artificial intelligence approach of bivariate statistical-methods-based kernel logistic regression classifier for landslide susceptibility modeling. Bulletin of Engineering Geology and the Environment, 78(6), 4397-4419.
8. Dauvergne, P. (2020). Is artificial intelligence greening global supply chains? Exposing the political economy of environmental costs. Review of International Political Economy, 1-23.
9. Elkatatny, S., Mahmoud, M., Tariq, Z., & Abdulraheem, A. (2018). New insights into the prediction of heterogeneous carbonate reservoir permeability from well logs using artificial intelligence network. Neural Computing and Applications, 30(9), 2673-2683.
10. Elzenary, M., Elkatatny, S., Abdelgawad, K. Z., Abdulraheem, A., Mahmoud, M., & Al-Shehri, D. (2018, August). New Technology to Evaluate Equivalent Circulating Density While Drilling Using Artificial Intelligence. In SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition. Society of Petroleum Engineers.
11. Flores, V., Keith, B., & Leiva, C. (2020). Using artificial intelligence techniques to improve the prediction of copper recovery by leaching. Journal of Sensors, 2020.
12. Gerassis, S., Saavedra, Á., Taboada, J., Alonso, E., & Bastante, F. G. (2019). Differentiating between fatal and non-fatal mining accidents using artificial intelligence techniques. International Journal of Mining, Reclamation and Environment, 1-13.

13. Gokhberg, L., Kuzminov, I., Khabirova, E., & Thurner, T. (2020). Advanced text-mining for trend analysis of Russia's Extractive Industries. Futures, 115, 102476.
14. Guo, H., Nguyen, H., Vu, D. A., & Bui, X. N. (2019). Forecasting mining capital cost for open-pit mining projects based on artificial neural network approach. Resources Policy, 101474.
15. Hao, H., Guo, R., Gu, Q., & Hu, X. (2019). Machine learning application to automatically classify heavy minerals in river sand by using SEM/EDS data. Minerals Engineering, 143, 105899.
16. Karatzoglou, I., Smart mining: How artificial intelligence can benefit the mining industry, Prescouter, August 2020. https://www.prescouter.com/2020/08/smart-mining-how-artificial-intelligence-can-benefit-the-mining-industry/
17. Kshetri, N. (2019). Complementary and Synergistic Properties of Blockchain and Artificial Intelligence. IT Professional, 21(6), 60-65.
18. Leiviskä, K. (2016, September). APPLICATION VIEWPOINTS OF EXPERT SYSTEMS IN MINERAL~{j·'METAL PROCESSING. In Expert Systems in Mineral and Metal Processing: Proceedings of the IFAC Workshop, Espoo, Finland, 26-28 August 1991 (p. 191). Elsevier.
19. Linca, M., Nanescu, M. Artificial Intelligence Is Changing The Mining Industry - Examples Of Successful Applications, Dacian Consulting, 2020. https://daciandata.tech/artificial-intelligence-is-changing-the-mining-industry-examples-of-successful-applications/
20. Litvinenko, V. S. (2020). Digital economy as a factor in the technological development of the mineral sector. Natural Resources Research, 29(3), 1521-1541.
21. McCoy, J. T., & Auret, L. (2019). Machine learning applications in minerals processing: A review. Minerals Engineering, 132, 95-109.
22. Qi, C. C. (2020). Big data management in the mining industry. International Journal of Minerals, Metallurgy and Materials, 27(2), 131-139.
23. Qi, C. C. (2020). Big data management in the mining industry. International Journal of Minerals, Metallurgy and Materials, 27(2), 131-139.
24. Qi, C., Chen, Q., Fourie, A., & Zhang, Q. (2018). An intelligent modelling framework for mechanical properties of cemented paste backfill. Minerals Engineering, 123, 16-27.
25. Ren, Y., Liang, J., Su, J., Cao, G., & Liu, H. (2020). Data sharing mechanism of various mineral resources based on blockchain. Frontiers of Engineering Management, 7(4), 592-604.
26. Shokri, A., Ghazizadeh, Z., Piroozfar, S., & Tohidi, H. (2020). Design of An Intelligent Model for Strategic Planning in Mineral Holding: Case study, Shahab-Sang Holding.
27. Tuşa, L., Kern, M., Khodadadzadeh, M., Blannin, R., Gloaguen, R., & Gutzmer, J. (2020). Evaluating the performance of hyperspectral short-wave infrared sensors for the pre-sorting of complex ores using machine learning methods. Minerals Engineering, 146, 106150.
28. Wang, L., Ma, Y., Yan, J., Chang, V., & Zomaya, A. Y. (2018). pipsCloud: High performance cloud computing for remote sensing big data management and processing. Future Generation Computer Systems, 78, 353-368.
29. Williams, J. R., & Potter-McIntyre, S. L. (2018). Utilizing" Big Data" visualization techniques to identify spatial and mineralogical relationships in clay-bearing deposits. AGUFM, 2018, P43A-12.
30. Yan, Y., Mattisson, T., Moldenhauer, P., Anthony, E. J., & Clough, P. T. (2020). Applying machine learning algorithms in estimating the performance of heterogeneous, multi-component materials as oxygen carriers for chemical-looping processes. Chemical Engineering Journal, 387, 124072.
31. Zhang, H., Nguyen, H., Bui, X. N., Nguyen-Thoi, T., Bui, T. T., Nguyen, N., ... & Moayedi, H. (2020). Developing a novel artificial intelligence model to estimate the capital cost of mining projects using deep neural network-based ant colony optimization algorithm. Resources Policy, 66, 101604.

NON-FERROUS METALS SECTOR

1. Caiazzo, F., & Caggiano, A. (2018). Laser direct metal deposition of 2024 Al alloy: trace geometry prediction via machine learning. Materials, 11(3), 444.
2. del Campo, G., Calatrava, S., Cañada, G., Olloqui, J., Martinez, R., & Santamaria, A. (2018, June). Iot solution for energy optimization in industry 4.0: Issues of a real-life implementation. In 2018 Global Internet of Things Summit (GIoTS) (pp. 1-6). IEEE.
3. Gomberg, J. A., Medford, A. J., & Kalidindi, S. R. (2017). Extracting knowledge from molecular mechanics simulations of grain boundaries using machine learning. Acta Materialia, 133, 100-108.
4. Guo, S., Li, T., & Zhou, K. (2017, December). An improved case retrieval method for the production manufacturing process of aluminum electrolysis. In 2017 International Conference on Industrial Informatics-Computing Technology, Intelligent Technology, Industrial Information Integration (ICIICII) (pp. 16-20). IEEE.
5. Kolokas, N., Vafeiadis, T., Ioannidis, D., & Tzovaras, D. (2020). Fault Prognostics in Industrial Domains using Unsupervised Machine Learning Classifiers. Simulation Modelling Practice and Theory, 102109.
6. Kruglov, I., Sergeev, O., Yanilkin, A., & Oganov, A. R. (2017). Energy-free machine learning force field for aluminum. Scientific reports, 7(1), 1-7.
7. Lan, W., Wu, A., & Yu, P. (2020). Development of a new controlled low strength filling material from the activation of copper slag: Influencing factors and mechanism analysis. Journal of Cleaner Production, 246, 119060.
8. Li, L., Xie, Y., Chen, X., Yue, W., & Zeng, Z. (2020). Dynamic uncertain causality graph based on cloud model theory for knowledge representation and reasoning. International Journal of Machine Learning and Cybernetics, 1-19.
9. Mulero, M. A., Zapata, J., Vilar, R., Martínez, V., & Gadow, R. (2015). Automated image inspection system to quantify thermal spray splat morphology. Surface and Coatings Technology, 278, 1-11.
10. Penciuc, D., Le Duigou, J., Daaboul, J., Eynard, B., & Vallet, F. (2016). Product Lifecycle Management Approach for Integration of Engineering Design and Lifecycle Engineering.
11. Perzyk, M., Dybowski, B., & Kozłowski, J. (2019). Introducing advanced data analytics in perspective of industry 4.0 in a die casting foundry. Archives of Foundry Engineering, 53-57.
12. Sarnovsky, M., Bednar, P., & Smatana, M. (2018). Big data processing and analytics platform architecture for process industry factories. Big Data and Cognitive Computing, 2(1), 3.
13. Sun, E., Wang, M., Li, Z., Li, J., & Gao, D. (2020, June). Diagnosis and Decision Analysis System of High Temperature Molten Aluminum Cell based on Neural Network. In 2020 IEEE 4th Information Technology, Networking, Electronic and Automation Control Conference (ITNEC) (Vol. 1, pp. 1624-1628). IEEE.
14. Taheri, K., Hasanipanah, M., Golzar, S. B., & Abd Majid, M. Z. (2017). A hybrid artificial bee colony algorithm-artificial neural network for forecasting the blast-produced ground vibration. Engineering with Computers, 33(3), 689-700.
15. Vitola, J., Pozo, F., Tibaduiza, D. A., & Anaya, M. (2017). Distributed piezoelectric sensor system for damage identification in structures subjected to temperature changes. Sensors, 17(6), 1252.
16. Wen, C., Zhang, Y., Wang, C., Xue, D., Bai, Y., Antonov, S., ... & Su, Y. (2019). Machine learning assisted design of high entropy alloys with desired property. Acta Materialia, 170, 109-117.
17. Zedel, H., Fritzsch, R., Akhtar, S., & Aune, R. E. (2019). Estimation of Aluminum Melt Filtration Efficiency Using Automated Image Acquisition and Processing. In Light Metals 2019 (pp. 1113-1120). Springer, Cham.

ENGINEERING SECTOR - AI

1. Almuiet, Mohammad Zayed, and Farah Zawaideh. "Intelligent agent framework for knowledge acquisition in supply chain management." International Journal of Scientific and Technology Research 8.9 (2019): 1984-1990.
2. Alvares, Alberto J., and Ricardo Gudwin. "Integrated System of Predictive Maintenance and Operation of Eletronorte Based on Expert System." IEEE Latin America Transactions 17.01 (2019): 155-166.
3. Aydoğan, Sena, Gül E. Okudan Kremer, and Diyar Akay. "Linguistic summarization to support supply network decisions." Journal of Intelligent Manufacturing (2020): 1-14.
4. Azadi, Majid, and Reza Farzipoor Saen. "A new data envelopment analysis model for evaluating the performance of expert systems in supply chain management." International Journal of Operational Research 30.1 (2017): 65-82.
5. Brazhenenko, M., Kozachok, P., Petrivskyi, V., Bychkov, O., & Shevchenko, V. (2019). Cloud based architecture design of system of systems. Paper presented at the 2019 15th International Conference on the Experience of Designing and Application of CAD Systems, CADSM 2019 - Proceedings, doi:10.1109/CADSM.2019.8779307
6. Chen, Yeh-cheng, et al. "Using case-based reasoning method to design a return merchandise authorization system for supply chain management in Internet of Thing." 2017 IEEE 17th International Conference on Communication Technology (ICCT). IEEE, 2017.
7. Chiu, Yu-Chen, Fan-Tien Cheng, and Hsien-Cheng Huang. "Developing a factory-wide intelligent predictive maintenance system based on Industry 4.0." Journal of the Chinese Institute of Engineers 40.7 (2017): 562-571.
8. Fink, Klaus, et al. "Dynamic Value Stream Optimization for Manual Assembly in the Learning Factory for Cyber-Physical Production Systems." Procedia Manufacturing 45 (2020): 78-83.
9. Herrera, M., Pérez-Hernández, M., Parlikad, A. K., & Izquierdo, J. (2020). Multi-agent systems and complex networks: Review and applications in systems engineering. Processes, 8(3) doi:10.3390/pr8030312
10. Hielata, K. "Complementing the Scoping Process of Configuration Projects by Design Thinking." Transdisciplinary Engineering for Complex Socio-technical Systems: Proceedings of the 26th ISTE International Conference on Transdisciplinary Engineering, July 30–August 1, 2019. Vol. 10. IOS Press, 2019.
11. Huang, Zhuoyu, et al. "Smart manufacturing and DVSM based on an Ontological approach." Computers in Industry 117 (2020): 103189.
12. Kaddari, Zakaria, et al. "Natural Language Processing: Challenges and Future Directions." International Conference on Artificial Intelligence & Industrial Applications. Springer, Cham, 2020.
13. Kalra, S., Gupta, S., & Prasad, J. S. (2019). Short term stock movements with big data and market sentiments analytics. International Journal of Innovative Technology and Exploring Engineering, 8(9), 2305-2313. doi:10.35940/ijitee.i8474.078919
14. Khripchenko, M., Novikov, A., Goncharov, A., & Snyatkov, E. (2019). Reducing the impact of transport machinery and equipment on the environment during reforestation: An innovative approach. Paper presented at the Proceedings of the 33rd International Business Information Management Association Conference, IBIMA 2019: Education Excellence and Innovation Management through Vision 2020, 2438-2445.
15. Kłos, S. (2016). A model of an ERP-based knowledge management system for engineer-to-order enterprises doi:10.1007/978-3-319-46254-7_4
16. Lee, YoonSang, and Riyaz Sikora. "Design of intelligent agents for supply chain management." Workshop on E-Business. Springer, Cham, 2015.

17. Leitão, Paulo, et al. "Intelligent products: The grace experience." Control Engineering Practice 42 (2015): 95-105.
18. Li, Xiang, Guodong Jia, and Weihua Wang. "Application of equipment integrity management expert system based on predictive maintenance." Structural Health Monitoring and Integrity Management: Proceedings of the 2nd International Conference of Structural Health Monitoring and Integrity Management (ICSHMIM 2014), Nanjing, China, 24-26 September 2014. CRC Press, 2015.
19. Lv, Z. -., Song, Y. -., & Lan, J. (2016). Feature-based optimization mechanism of stamping process for automobile panels. Suxing Gongcheng Xuebao/Journal of Plasticity Engineering, 23(3), 46-52. doi:10.3969/j.issn.1007-2012.2016.03.009
20. Marçal, Hatakeyama. "Expert System based on Fuzzy rules for predictive monitoring and planning of maintenance in rotating machines." International Foundation for Production Research (IFPR), 2015.
21. Meesublak, Koonlachat, and Tosapol Klinsukont. "A Cyber-Physical System Approach for Predictive Maintenance." 2020 IEEE International Conference on Smart Internet of Things (SmartIoT). IEEE, 2020.
22. Ni, Wang, et al. "An online matching customized method facing customers' needs." Chongqing yi ke da xue, di 2 lin chuang xue yuan Bing du xing gan yan yan jiu suo, 2017.
23. Ni, Du, Zhi Xiao, and Ming K. Lim. "A systematic review of the research trends of machine learning in supply chain management." International Journal of Machine Learning and Cybernetics (2019): 1-20.
24. Park, J., Ferguson, M., & Law, K. H. (2018). Data driven analytics (machine learning) for system characterization, diagnostics and control optimization doi:10.1007/978-3-319-91635-4_2
25. Runji, Joel Murithi, and Chyi-Yeu Lin. "Markerless cooperative augmented reality-based smart manufacturing double-check system: Case of safe PCBA inspection following automatic optical inspection." Robotics and Computer-Integrated Manufacturing 64 (2020): 101957.
26. Shcherbakov, Maxim V., Artem V. Glotov, and Sergey V. Cheremisinov. "Proactive and predictive maintenance of cyber-physical systems." Cyber-Physical Systems: Advances in Design & Modelling. Springer, Cham, 2020. 263-278.
27. Smoker, Thomas M., et al. "Applying cognitive computing to maintainer-collected data." 2017 2nd International Conference on System Reliability and Safety (ICSRS). IEEE, 2017.
28. Tsai, Yu-Ting, et al. "Utilization of a reinforcement learning algorithm for the accurate alignment of a robotic arm in a complete soft fabric shoe tongues automation process." Journal of Manufacturing Systems 56 (2020): 501-513.
29. Usama, M., Qadir, J., Raza, A., Arif, H., Yau, K. -. A., Elkhatib, Y., . . . Al-Fuqaha, A. (2019). Unsupervised machine learning for networking: Techniques, applications and research challenges. IEEE Access, 7, 65579-65615. doi:10.1109/ACCESS.2019.2916648
30. Verhagen, Oudkerk. "Use of textual elements to improve reliability prediction for aircraft component behavior." IOS Press BV, 2020.
31. Von Birgelen, Alexander, et al. "Self-organizing maps for anomaly localization and predictive maintenance in cyber-physical production systems." Procedia CIRP 72 (2018): 480-485.
32. Wang, Ye, and Denial Wang. "Multi-agent based intelligent supply chain management." Proceedings of the Ninth International Conference on Management Science and Engineering Management. Springer, Berlin, Heidelberg, 2015.
33. Wang, Pengjia, et al. "Applying CBR to machine tool product configuration design oriented to customer requirements." Chinese Journal of Mechanical Engineering 30.1 (2017): 60-76.
34. Wang, Jinjiang, et al. "A new paradigm of cloud-based predictive maintenance for intelligent manufacturing." Journal of Intelligent Manufacturing 28.5 (2017): 1125-1137.

35. Wang, Yue, Xiang Li, and Fugee Tsung. "Configuration-Based Smart Customization Service: A Multitask Learning Approach." IEEE Transactions on Automation Science and Engineering (2020).
36. Waris, Mohammad Maqbool, Cesar Sanin, and Edward Szczerbicki. "Smart innovation engineering (SIE): experience-based product innovation system for industry 4.0." International Conference on Information Systems Architecture and Technology. Springer, Cham, 2017.
37. Wichmann, Pascal, et al. "Towards automatically generating supply chain maps from natural language text." IFAC-PapersOnLine 51.11 (2018): 1726-1731.
38. Wichmann, Pascal, et al. "Extracting supply chain maps from news articles using deep neural networks." International Journal of Production Research (2020): 1-17.
39. Yang, Fang-Ning, and Huei-Yung Lin. "Development of A Predictive Maintenance Platform for Cyber-Physical Systems." 2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS). IEEE, 2019.
40. Zanon, Lucas Gabriel, et al. "A decision making model based on fuzzy inference to predict the impact of SCOR® indicators on customer perceived value." International Journal of Production Economics 223 (2020): 107520.
41. Zhang, R., Phillips, B. M., Fernández-Cabán, P. L., & Masters, F. J. (2019). Cyber-physical structural optimization using real-time hybrid simulation. Engineering Structures, 195, 113-124. doi:10.1016/j.engstruct.2019.05.042
42. Zhou, J., Huang, B., & Jiang, W. (1994). Development of urea production expert system. Hua Dong Li Gong Da Xue/Journal of East China University of Science and Technology, 20(2), 205-209.
43. Zhu, Lou, Li, Dong. "Product customization method based on extension design." CIMS, 2020.

ENGINEERING SECTOR – BD

44. Bagheri, H., & Shaltooki, A. A. (2015). Big data: Challenges, opportunities and cloud based solutions. International Journal of Electrical and Computer Engineering, 5(2), 340-343. doi:10.11591/ijece.v5i2.pp340-343
45. Balasubramanyam, K. (2020). Adaptation of block chain technology in manufacturing sector. Paper presented at the 2020 International Conference on Mainstreaming Block Chain Implementation, ICOMBI 2020, doi:10.23919/ICOMBI48604.2020.9203545
46. Beneventi, F., Bartolini, A., Cavazzoni, C., & Benini, L. (2017). Continuous learning of HPC infrastructure models using big data analytics and in-memory processing tools. Paper presented at the Proceedings of the 2017 Design, Automation and Test in Europe, DATE 2017, 1038-1043. doi:10.23919/DATE.2017.7927143
47. Cheng, D. -., Zhang, J., Hu, Z. -., Xu, S. -., & Fang, X. -. (2020). A digital twin-driven approach for on-line controlling quality of marine diesel engine critical parts. International Journal of Precision Engineering and Manufacturing, 21(10), 1821-1841. doi:10.1007/s12541-020-00403-y
48. Colombo, E. F., Shougarian, N., Sinha, K., Cascini, G., & de Weck, O. L. (2020). Value analysis for customizable modular product platforms: Theory and case study. Research in Engineering Design, 31(1), 123-140. doi:10.1007/s00163-019-00326-4
49. Del Vecchio, Pasquale, et al. "Big data for open innovation in SMEs and large corporations: Trends, opportunities, and challenges." Creativity and Innovation Management 27.1 (2018): 6-22.
50. Detzner, A., & Eigner, M. (2018). A digital twin for root cause analysis and product quality monitoring. Paper presented at the Proceedings of International Design Conference, DESIGN, , 4 1547-1558. doi:10.21278/idc.2018.0418
51. Feng, Q., & Shanthikumar, J. G. (2018). How research in production and operations management may evolve in the era of big data. Production and Operations Management, 27(9), 1670-1684. doi:10.1111/poms.12836

52. Salierno, Giulio, et al. "An Architecture for Predictive Maintenance of Railway Points Based on Big Data Analytics." International Conference on Advanced Information Systems Engineering. Springer, Cham, 2020.
53. Truong, Hong-Linh. "Integrated analytics for IIoT predictive maintenance using IoT big data cloud systems." 2018 IEEE International Conference on Industrial Internet (ICII). IEEE, 2018.
54. Weerasinghe, Shakthi, and Supunmali Ahangama. "Predictive Maintenance and Performance Optimisation in Aircrafts using Data Analytics." 2018 3rd International Conference on Information Technology Research (ICITR). IEEE, 2018.
55. Ye, Y., Yang, D., & Jiang, Z. (2006). Configuration knowledge modeling of customizable products based on semantic web technologies. Journal of Southeast University (English Edition), 22(3), 418-422.

WATER SECTOR

1. Ponce Romero, J. M., Hallett, S. H., & Jude, S. (2017). Leveraging big data tools and technologies: addressing the challenges of the water quality sector. Sustainability, 9(12), 2160.
2. Ostojin, S., Shepherd, W., Williams, K., Simões, N., & Steinhardt, J. (2017, November). CENTAUR: smart utilisation of wastewater storage capacity to prevent flooding. In Proceedings of CIWEM Urban Drainage Group autumn conference and exhibition.
3. Howell, S., Rezgui, Y., & Beach, T. (2018). Water utility decision support through the semantic web of things. *Environmental Modelling & Software*, *102*, 94-114.
4. dos Santos, F. C. R., Librantz, A. F. H., Dias, C. G., & Rodrigues, S. G. (2017). < b> Intelligent system for improving dosage control. Acta Scientiarum. Technology, 39(1), 33-38.
5. Chen, Y., & Han, D. (2016). Big data and hydroinformatics. *Journal of Hydroinformatics*, *18*(4), 599-614.
6. Nicolae, A., Korodi, A., & Silea, I. (2019). Identifying Data Dependencies as First Step to Obtain a Proactive Historian: Test Scenario in the Water Industry 4.0. *Water*, *11*(6), 1144.
7. Mehr, A. D., Nourani, V., Kahya, E., Hrnjica, B., Sattar, A. M., & Yaseen, Z. M. (2018). Genetic programming in water resources engineering: A state-of-the-art review. *Journal of hydrology*, *566*, 643-667.
8. Ghernaout, D., Aichouni, M., & Alghamdi, A. (2018). Applying big data in water treatment industry: A new era of advance. *International Journal of Advanced and Applied Sciences*, *5*(3), 89-97.
9. Facchini, A., Scala, A., Lattanzi, N., Caldarelli, G., Liberatore, G., Dal Maso, L., & Di Nardo, A. (2016, October). Complexity science for sustainable smart water grids. In *Italian Workshop on Artificial Life and Evolutionary Computation* (pp. 26-41). Springer, Cham.
10. Sinha, S., & Sears, L. (2017). Collection and Compilation of Water Pipeline Field Performance Data. In *Pipelines 2017* (pp. 124-135).
11. Garrido-Baserba, M., Corominas, L., Cortés, U., Rosso, D., & Poch, M. (2020). The fourth-revolution in the water sector encounters the digital revolution. *Environmental Science & Technology*, *54*(8), 4698-4705.
12. Al Aani, S., Bonny, T., Hasan, S. W., & Hilal, N. (2019). Can machine language and artificial intelligence revolutionize process automation for water treatment and desalination?. *Desalination*, *458*, 84-96.
13. Tyralis, H., Papacharalampous, G., & Langousis, A. (2019). A brief review of random forests for water scientists and practitioners and their recent history in water resources. *Water*, *11*(5), 910.

14. Zhou, Y., Chang, L. C., Uen, T. S., Guo, S., Xu, C. Y., & Chang, F. J. (2019). Prospect for small-hydropower installation settled upon optimal water allocation: An action to stimulate synergies of water-food-energy nexus. *Applied Energy*, *238*, 668-682.
15. Hadjimichael, A., Comas, J., & Corominas, L. (2016). Do machine learning methods used in data mining enhance the potential of decision support systems? A review for the urban water sector. *AI Communications*, *29*(6), 747-756.
16. Naghibi, S. A., Hashemi, H., Berndtsson, R., & Lee, S. (2020). Application of extreme gradient boosting and parallel random forest algorithms for assessing groundwater spring potential using DEM-derived factors. *Journal of Hydrology*, *589*, 125197.
17. Bagloee, S. A., Asadi, M., & Patriksson, M. (2018). Minimization of water pumps' electricity usage: A hybrid approach of regression models with optimization. *Expert Systems with Applications*, *107*, 222-242.
18. Nikolopoulos, D., Moraitis, G., Bouziotas, D., Lykou, A., Karavokiros, G., & Makropoulos, C. (2020). Cyber-Physical Stress-Testing Platform for Water Distribution Networks. *Journal of Environmental Engineering*, *146*(7), 04020061.
19. Rossetto, R., De Filippis, G., Triana, F., Ghetta, M., Borsi, I., & Schmid, W. (2019). Software tools for management of conjunctive use of surface-and ground-water in the rural environment: integration of the Farm Process and the Crop Growth Module in the FREEWAT platform. *Agricultural Water Management*, *223*, 105717.

CHEMICAL SECTOR

1. Ighalo, J. O., Adeniyi, A. G., & Marques, G. (2020). Application of linear regression algorithm and stochastic gradient descent in a machine‐learning environment for predicting biomass higher heating value. *Biofuels, Bioproducts and Biorefining*.
2. McDonagh, J. L., Swope, W. C., Anderson, R. L., Johnson, M. A., & Bray, D. J. (2019). What Can Digitization Do For Formulated Product Innovation and Development?. *Polymer International*.
3. Wende, T. I. A. N., Zijian, L. I. U., Lening, L. I., ZHANG, S., & Li, C. (2020). (PSE) identification of abnormal conditions in high-dimensional chemical process based on feature selection and deep learning. *Chinese Journal of Chemical Engineering*.
4. Clark, R. D. (2020). Putting deep learning in perspective for pest management scientists. *Pest Management Science*.
5. Ding, J., Luo, Q., Jia, L., & You, J. (2020). Deep Forest-Based Fault Diagnosis Method for Chemical Process. *Mathematical Problems in Engineering*, *2020*.
6. Sabanci, K. (2020). Detection of sunn pest‐damaged wheat grains using artificial bee colony optimization‐based artificial intelligence techniques. *Journal of the Science of Food and Agriculture*, *100*(2), 817-824.
7. Blanco, D. E., Lee, B., & Modestino, M. A. (2019). Optimizing organic electrosynthesis through controlled voltage dosing and artificial intelligence. *Proceedings of the National Academy of Sciences*, *116*(36), 17683-17689.
8. Abbasi, M. R., Shamiri, A., Hussain, M. A., & Aghay Kaboli, S. H. (2019). Dynamic process modeling and hybrid intelligent control of ethylene copolymerization in gas phase catalytic fluidized bed reactors. *Journal of Chemical Technology & Biotechnology*, *94*(8), 2433-2451.
9. Piccione, P. M. (2019). Realistic interplays between data science and chemical engineering in the first quarter of the 21st century: Facts and a vision. *Chemical Engineering Research and Design*, *147*, 668-675.
10. Makarova, A. S., Jia, X., Kruchina, E. B., Kudryavtseva, E. I., & Kukushkin, I. G. (2019). Environmental performance assessment of the chemical industries involved in the Responsible Care® Program: Case study of the Russian Federation. *Journal of Cleaner Production*, *222*, 971-985.

11. Rendall, R., & Reis, M. S. (2018). Which regression method to use? Making informed decisions in "data-rich/knowledge poor" scenarios–The Predictive Analytics Comparison framework (PAC). *Chemometrics and Intelligent Laboratory Systems*, *181*, 52-63.
12. Li, M., Du, W., Qian, F., & Zhong, W. (2018). Total plant performance evaluation based on big data: Visualization analysis of TE process. *Chinese journal of chemical engineering*, *26*(8), 1736-1749.
13. Lu, B., & Chiang, L. (2018). Semi-supervised online soft sensor maintenance experiences in the chemical industry. *Journal of Process Control*, *67*, 23-34.
14. Pellis, A., Cantone, S., Ebert, C., & Gardossi, L. (2018). Evolving biocatalysis to meet bioeconomy challenges and opportunities. *New biotechnology*, *40*, 154-169.
15. Fernandez Nunez, E. G., Barchi, A. C., Ito, S., Escaramboni, B., Herculano, R. D., Mayer, C. R. M., & de Oliva Neto, P. (2017). Artificial intelligence approach for high level production of amylase using Rhizopus microsporus var. oligosporus and different agro-industrial wastes. *Journal of Chemical Technology & Biotechnology*, *92*(3), 684-692.
16. Khare, C., & Chin, S. T. (2017). Potential for data analytics opportunities in SMART chemical Industry. *CHIMICA OGGI-CHEMISTRY TODAY*, *35*(2), 60-61.
17. Choy, K. L., Ho, G. T. S., Lee, C. K. H., Lam, H. Y., Cheng, S. W., Siu, P. K., ... & Tsang, Y. P. (2016). A recursive operations strategy model for managing sustainable chemical product development and production. *International journal of production economics*, *181*, 262-272.
18. Ji, X., He, G., Xu, J., & Guo, Y. (2016). Study on the mode of intelligent chemical industry based on cyber-physical system and its implementation. *Advances in Engineering software*, *99*, 18-26.
19. Lele, Q., & Lihua, K. (2016). Technical framework design of safety production information management platform for chemical industrial parks based on cloud computing and the internet of things. *International Journal of Grid and Distributed Computing*, *9*(6), 299-314.
20. Tetko, I. V., Engkvist, O., Koch, U., Reymond, J. L., & Chen, H. (2016). BIGCHEM: challenges and opportunities for big data analysis in chemistry. *Molecular informatics*, *35*(11-12), 615-621.
21. Grigelova, V., Abasova, J., & Tanuska, P. (2019, April). Proposal of Data Pre-processing for Purpose of Analysis in Accordance with the Concept Industry 4.0. In *Computer Science On-line Conference* (pp. 324-331). Springer, Cham.
22. Chidepatil, A., Bindra, P., Kulkarni, D., Qazi, M., Kshirsagar, M., & Sankaran, K. (2020). From Trash to Cash: How Blockchain and Multi-Sensor-Driven Artificial Intelligence Can Transform Circular Economy of Plastic Waste?. *Administrative Sciences*, *10*(2), 23.
23. Kramer, A., & Morgado-Dias, F. (2020) Artificial intelligence in process control applications and energy saving: a review and outlook. *Greenhouse Gases: Science and Technology*.
24. Plehiers, P. P., Symoens, S. H., Amghizar, I., Marin, G. B., Stevens, C. V., & Van Geem, K. M. (2019). Artificial Intelligence in Steam Cracking Modeling: A Deep Learning Algorithm for Detailed Effluent Prediction. *Engineering*, *5*(6), 1027-1040.
25. Kubota, M., Takanashi, K., & Dunn, K. A. (2019, November). Investigation of Quantification of Agglomeration Level of Silica Particles in CMP Slurry for Creating the Quality Prediction Formula by AI Technology. In *2019 IEEE Albany Nanotechnology Symposium (ANS)* (pp. 1-4). IEEE.
26. Mazzali, D. G. Z., Franco, I. C., & Silva, F. V. (2018). Analysis of the Effects of Neuro-Fuzzy Control Configuration Parameters on PH Neutralization Process. *Chemical Product and Process Modeling*, *13*(4).
27. Bhuiya, M. B. (2016, September). Controlling Line Follower Robot with the Remote Web Server. In *Proceedings of SAI Intelligent Systems Conference* (pp. 559-583). Springer, Cham.
28. Appel, J., Colombo, C., Dätwyler, U., Chen, Y., & Kerimoglu, N. (2016). Comprehensive Analysis Competence and Innovative Approaches for Sustainable Chemical Production. *CHIMIA International Journal for Chemistry*, *70*(9), 621-627.
29. Watford, S., Edwards, S., Angrish, M., Judson, R. S., & Friedman, K. P. (2019). Progress in data interoperability to support computational toxicology and chemical safety evaluation. *Toxicology and applied pharmacology*, *380*, 114707.
30. Pendleton, I. M., Cattabriga, G., Li, Z., Najeeb, M. A., Friedler, S. A., Norquist, A. J., ... & Schrier, J. (2019). Experiment Specification, Capture and Laboratory Automation Technology (ESCALATE): a software pipeline for automated chemical experimentation and data management. *MRS Communications*, *9*(3), 846-859.

CERAMICS SECTOR

1. Aggour, K., Gupta, V., Ruscitto, D., Ajdelsztajn, L., Bian, X., Brosnan, K., Vinciquerra, J. (2019). Artificial intelligence/machine learning in manufacturing and inspection: A GE perspective. MRS Bulletin, 44(7), 545-558.
2. Baturynska, I., Semeniuta, O., Martinsen, K. (2018) Optimization of Process Parameters for Powder Bed Fusion Additive Manufacturing by Combination of Machine Learning and Finite Element Method: A Conceptual Framework. Procedia CIRP 67, 227-232.
3. Boral, S, & Chakraborty, S. (2016). A case-based reasoning approach for non-traditional machining processes selection. Advances in Production Engineering & Management 11, 311-323.
4. Braccini, A.M., Margherita, E.G. (2019). Exploring Organizational Sustainability of Industry 4.0 under the Triple Bottom Line: The Case of a Manufacturing Company. Sustainability 11, 36.
5. Cunha, R., et al., (2018). Applying Non-destructive Testing and Machine Learning to Ceramic Tile Quality Control. 2018 VIII Brazilian Symposium on Computing Systems Engineering (SBESC), Salvador, Brazil, pp. 54-61.
6. De Guire, E, Bartolo, L, Brindle, R, et al. (2019). Data-driven glass/ceramic science research: Insights from the glass and ceramic and data science/informatics communities. J Am Ceram Soc. 102: 6385– 6406.
7. Diao, S., Chen, X., Wu, L., Yang, M., Liu, J. (2017). The Optimal Collision Avoidance Trajectory Planning of Redundant Manipulators in the Process of Grinding Ceramic Billet Surface. Mathematical Problems in Engineering 2017, Article ID 7405831.
8. Eckel, Z.C., Zhou, C., Martin, J.H., Jacobsen, A.J., Carter, W.B., Schaedler, T.A. (2016). Additive manufacturing of polymer-derived ceramics. Science 351, Issue 6268, 58-62.
9. Faisal, Md., & Katiyar, V. (2016). Identification of essential requirements of IOT and big data analytics to extend ceramic manufacturing. International Journal of Engineering Sciences & Research Technology (IJESRT) 5, No. 12.
10. Ghayour, H., Abdellahi, M., Bahmanpour, M. (2015). Artificial intelligence and ceramic tools: Experimental study, modeling and optimizing. Ceramics International 41, Issue 10, Part A, 13470-13479.
11. Hanzaei, S.H., Afshar, A., Barazandeh, R. (2017). Automatic detection and classification of the ceramic tiles' surface defects. Pattern Recognition 66, 174-189.
12. Kesharaju, M., Nagarajah, R., Zhang, T., Crouch, I. (2014), Ultrasonic sensor based defect detection and characterisation of ceramics, Ultrasonics 54-1, 312-317.
13. Kowalski, A., Rosienkiewicz, M. (2017.) ANN-Based Hybrid Algorithm Supporting Composition Control of Casting Slip in Manufacture of Ceramic Insulators. In: Graña M., López-Guede J., Etxaniz O., Herrero Á., Quintián H., Corchado E. (eds) International Joint Conference SOCO'16-CISIS'16-ICEUTE'16. SOCO 2016, CISIS 2016, ICEUTE 2016. Advances in Intelligent Systems and Computing, vol 527. Springer, Cham.
14. Lang, V., Weingarten, S., Wiemer, H., Scheithauer, U., Glausch, F., Johne, R., Michaelis, A., Ihlenfeldt, S. (2020). Process Data-Based Knowledge Discovery in Additive Manufacturing of Ceramic Materials by Multi-Material Jetting (CerAM MMJ). J. Manuf. Mater. Process. 4, 74.
15. Ma, S., Zhang, Y., Liu, Y., Yang, H., Lv, J., Ren, S. (2020). Data-driven sustainable intelligent manufacturing based on demand response for energy-intensive industries. Journal of Cleaner Production 274, 123155.
16. Min, B., Tin, H., Nasridinov, A., Yoo, K. (2020). Abnormal Detection and Classification in i-Ceramic Images. 2020 IEEE International Conference on Big Data and Smart Computing (BigComp), Busan, Korea (South), 17-18.
17. Nakai, M.E., Aguiar P.R., Guillardi, H., Bianchi, E.C., Spatti D.H., D'Addona, D.M. (2015). Evaluation of neural models applied to the estimation of tool wear in the grinding of advanced ceramics. Expert Systems with Applications 42, Issue 20, 7026-7035.
18. Park, Y., Hyun S., Hong, Y.W. (2019). A Stochastic Model for Virtual Data Generation of Crack Patterns in the Ceramics Manufacturing Process. Journal of the Korean Ceramic Society 56, Issue 6, 596-600.
19. Pimenov, D.Y., Bustillo, A. & Mikolajczyk, T. (2018). Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. J Intell Manuf 29, 1045–1061.

20. Qian, Z., QingLong, M., YongQian, X., Gan Lin, G. (2020). The Robot Intelligent Spraying Glazing System for Sanitary Ceramics Industry. J. Phys.: Conf. Ser. 1653 012028
21. Ruggieri, A., Braccini, A.M., Poponi, S., Mosconi, E.M. (2016). A Meta-Model of Inter-Organisational Cooperationfor the Transition to a Circular Economy. Sustainability 8, 1153.
22. Sadegh Amalnik, M. (2018). 'Expert System Approach for Optimization of Design and Manufacturing Process for Rotary Ultrasonic Machining', ADMT Journal, 11(1), pp. 1-13..
23. Shi. Y., Zhang, Y., Baek, S., De Backer, W., Harik, R. (2018), Manufacturability analysis for additive manufacturing using a novel feature recognition technique, Computer-Aided Design and Applications, 15:6, 941-952.
24. Travitzky, N., Bonet, A., Dermeik, B., Fey, T., Filbert-Demut, I., Schlier, L., Schlordt, T. and Greil, P. (2014). Additive Manufacturing of Ceramic-Based Materials. Adv. Eng. Mater., 16, 729-754.
25. Tripathi, G., Anowarul, H., Agarwal, K., Prasad, D.K. (2019). Classification of Micro-Damage in Piezoelectric Ceramics Using Machine Learning of Ultrasound Signals. Sensors 19, 4216.
26. Wang, J., Huang, J., Chen,W., Liu, J., Xu, D. (2016). Design of IoT-based energy efficiency management system for building ceramics production line. 2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA), Hefei, 912-917
27. Yuan, R., Tian, Y., Xue, D., Xue, D., Zhou, Y., Ding, X., Sun, J., Lookman, T. (2019). Accelerated Search for BaTiO3-Based Ceramics with Large Energy Storage at Low Fields Using Machine Learning and Experimental Design. Adv. Sci. 6, 1901395.

CEMENT SECTOR

1. Chen, P. C., Liu, K. H., & Ma, H. W. (2017). Resource and waste-stream modeling and visualization as decision support tools for sustainable materials management. Journal of Cleaner Production, 150, 16-25.
2. Contreras, J., Bogaerts, M., Griffin, D., Rodriguez, F., Sianipar, S., Villar, V., & Taoutaou, S. (2017, May). Real-Time Monitoring and Diagnoses on Deepwater Cement Barrier Placement: Case Studies from the Gulf of Mexico and Atlantic Canada. In Offshore Technology Conference. Offshore Technology Conference.
3. DeRousseau, M. A., Kasprzyk, J. R., & Srubar III, W. V. (2018). Computational design optimization of concrete mixtures: A review. Cement and Concrete Research, 109, 42-53.
4. Egilmez, G., Ghani, N. M. A. M. A., & Gedik, R. (2017). Layer analysis of CO2 sources in the US economic supply chains: an input output LCA study. Industrial Management & Data Systems.
5. Fu, D., Song, P., Zhang, X., & Liu, G. (2020, July). Research on Soft Measurement Method of Temperature Field in Cement Rotary Kiln. In 2020 39th Chinese Control Conference (CCC) (pp. 5939-5942). IEEE.
6. Gulbandilar, E., & Kocak, Y. (2016). Application of expert systems in prediction of flexural strength of cement mortars. Computers and Concrete, 18(1), 1-16.
7. Jena, M. C., Mishra, S. K., & Moharana, H. S. (2020). Application of Industry 4.0 to enhance sustainable manufacturing. Environmental Progress & Sustainable Energy, 39(1), 13360.
8. Li, S., Li, R., & Liu, W. (2016, August). The application of expert system and fuzzy control system in cement grate cooler system. In 2016 7th IEEE International Conference on Software Engineering and Service Science (ICSESS) (pp. 770-773). IEEE.
9. Liu, H. R., Lv, X. H., Li, X., Li, S. Z., & Shi, Y. H. (2015, September). Investigation of Fault Diagnosis Model of Rotary Kiln Based on Improved Algorithm of Bayesian. In 2015 Fifth International Conference on Instrumentation and Measurement, Computer, Communication and Control (IMCCC) (pp. 1600-1605). IEEE.
10. Marani, A., & Nehdi, M. L. (2020). Machine learning prediction of compressive strength for phase change materials integrated cementitious composites. Construction and Building Materials, 265, 120286.

11. Ning, F., Yu, H., & Lu, S. (2019, June). Research on Given Algorithm of Temperature Setting Value of Cement Rotary Kiln Firing Zone Based on Case-based Reasoning. In 2019 Chinese Control And Decision Conference (CCDC) (pp. 500-505). IEEE.
12. Saffari, A., Ataei, M., Sereshki, F., & Naderi, M. (2019). Environmental impact assessment (EIA) by using the Fuzzy Delphi Folchi (FDF) method (case study: Shahrood cement plant, Iran). Environment, Development and Sustainability, 21(2), 817-860.
13. Teja, R., Sridhar, P., & Guruprasath, M. (2016). Control and optimization of a triple string rotary cement kiln using model predictive control. IFAC-PapersOnLine, 49(1), 748-753.
14. Torres, J. L., Martinez, F., Yepez, S. X., Cardoso, O. F., Moretti, F., & Contreras Escalante, J. R. (2017, March). Real-Time Monitoring Enables Control and Evaluation of Cementing Operations. In SPE Latin America and Caribbean Mature Fields Symposium. Society of Petroleum Engineers.
15. Vargas, P., Restrepo-Baena, O., & Tobón, J. I. (2017). Microstructural analysis of interfacial transition zone (ITZ) and its impact on the compressive strength of lightweight concretes. Construction and Building Materials, 137, 381-389.
16. Yaseen, Z. M., Deo, R. C., Hilal, A., Abd, A. M., Bueno, L. C., Salcedo-Sanz, S., & Nehdi, M. L. (2018). Predicting compressive strength of lightweight foamed concrete using extreme learning machine model. Advances in Engineering Software, 115, 112-125.
17. Zhou, P., & Yuan, M. (2014, June). Intelligent dynamic modeling for online estimation of burning zone temperature in cement rotary kiln. In Proceeding of the 11th World Congress on Intelligent Control and Automation (pp. 6167-6171). IEEE.

9. ANNEXES

9.1 ANNEX – DETAILED SECTOR BY SECTOR LITERATURE REVIEW

In the following section we provide the detailed literature review for each of the 8 SPIRE sectors considered in the AI-CUBE project (cement, ceramics, chemicals, engineering, minerals, non-ferrous metals, steel and water). This corresponds to the statistics and summaries presented in Section 5.3 and 6.1 of this document.

Within each sector, each process is evaluated in turn: Market trends and open innovation, Product design, Predictive maintenance, Supply chain management (re) configuring and scheduling, (Model predictive) process control and optimization, Research and innovation management, planning and design.

Note that the literature search in this Section is not limited to only European references, and includes numerous papers from all around the world, where the United States and China are particularly active. We state that this is a true reflection of the real situation, as academic repository and database searches based mainly on technology, process and sector keywords retrieve these results. Also, many publications have co-authors with affiliations from multiple countries around the globe, hence it is difficult to categorize the publications based on geographical region. In other sections EU projects, roadmaps and activity are considered exclusively. In following subsections of Section 5 of the document we provide a summary and comparison of EU projects vs International (non EU).

9.1.1 Water sector

Firstly, for the supply chain (re)configuring and scheduling process, Machine Learning Technologies and techniques are applied in general to improve energy and resource efficiency in the water distribution systems (Bagloee et al. 2018) and reduce the costs of raw material in water treatment plants (dos Santos et al. 2017). The goals of sustainability and efficiency appear to be the most pursued ones, even through the application of Intelligent Systems technologies to optimize multi-sectoral water allocation (Zhou et al. 2019).

In the model predictive process control and optimization area, AI is applied in Natural Language processing technologies for complex systems and management science, to reshape and optimize the performance of the water infrastructure resilience (Facchini et al. 2016). Object and spatial recognition technologies such as GIS-integrated simulation models have been developed for the conjunctive use of surface water and groundwater and water-constrained agricultural production (Rossetto et al. 2019).

Most of the papers retrieved focused on Machine Learning technology applications such as genetic programming for water resource engineering (Mehr et al. 2018), process automation in desalination (Al Aani et al. 2019), and Random Forest algorithms for water resource applications (Tyralis et al. 2019). Researchers also developed Intelligent Planning AI technologies for the smart utilisation of wastewater storage capacity to prevent flooding (Ostojin et al. 2017), and cyber-physical systems, in the development of a stress-testing platform for water utilities (Nikolopoulos et al. 2020).

In the application of BD technologies, the literature found has been seen to focus on data processing, applying BD for monitoring and control purposes (Nicolae et al. 2019), data collection and BD analytics for water pipeline infrastructure systems (Sinha & Sears, 2017). BD is also applied for data visualisation to enhance the understanding of contaminants in wastewater (Romero et al. 2017).

In the process of Research and innovation management, planning and design, we found papers focused on Machine Learning, Data visualization and management. ML technologies apply artificial neural networks as decision support systems in the water and wastewater sectors (Hadjimichael et al. 2016), and a groundwater resource dataset was built specifically for ML use (Naghibi et al. 2020). Scholars combined BD analytics (including AI) with existing and future urban water infrastructure (Garrido-Baserba et al. 2020). Finally, research focused on the application of data management techniques to use BD for hydro informatics (Chen & Han, 2016), develop a water knowledge management platform extending the Internet of Things towards a Semantic Web of Things (Howell et al. 2018), and rely on AI&BD for decision making (Ghernaout et al. 2018) in the water industry processes.

9.1.2 Steel sector

For the processes of “Market trend and open innovation” and “research and innovation management”, at present no papers dedicated to the development of AI and BD solutions were found clearly relating to them. Instead, for the other macro processes, the analyzed papers discuss different aspects and present solutions and advanced tools able to improve the performance of the process in the steel sector.

For what concerns the “product customization/design”, for example the NPL technology is used for the entity recognition of the steel product category (Chenhao and Chengyao, 2019) or it is included in a deep learning framework for the history dependent response prediction, which aims to analyze the mechanical characteristics of the steel product (Wang et al., 2020). Machine learning is used for predictive models for fatigue property analysis (Zhang et al., 2018) and for a model to predict the tensile strength of steel rods manufactured in an electric arc furnace (Ruiz et al., 2020); machine learning is used also for the development of digital twin models for order, design, purchase and scheduling for specific manufacturing processes in the steel product life cycle (Xiang et al., 2018). Moreover, as presented in Kang et al. (2018), a vision-based automatic identification tracking method is utilized to identity a steel product achieved by automatically and deeply learning visual features from the steel image without needing to embed any identification code onto the product surfaces. Finally, Expert Systems are also implemented to analyze the quality of the steel products: in Kong et al. (2019), for the analysis of metallurgical processes related to continuous casting with an abnormal casting event, an Expert System allowed the use of the internal crack generation index of the slice unit to predict the crack occurrence rating of each sized slab. Another example of a product quality prediction model is provided by Klinger et al., (2017) with a modular system architecture and process information and data management system based on the physical and chemical principles; it provides an extremely high level of predictive precision in comparison with the measurements based on laboratory conditions.

In the “predictive maintenance” area, the use of neural networks methods and deep learning enable earlier prediction of systems failure (Karagiorgou et al, 2019). For example, in Lahamdi et al (2018) these technologies allow to estimate the remaining useful life of composite drill pipe subjected to cyclic loads; or predictive models evaluate the gradual degradation of machinery, permitting the operators to make informed decisions regarding maintenance operations as described in Ruiz-Sarmiento et al., (2020); in Trian et al. (2014) a neural network-based solutions is developed for crack prediction to improve the steel-casting process performance by decreasing the number of crack-generated failure cases. Moreover, Kim et al (2018) proposed a framework based on CPS and a knowledge-based system to detect functional failure that reduces the time of human expertise acquisition and the cost of solving over-generalization and over-fitting problems. Also, Expert Systems are implemented for the predictive maintenance: in Hu et al (2020) data mining and Expert Systems create a default diagnosis model for steel ladle turret bearing saving tremendous time for steel mill's decisive equipment maintenance by precisely predicting the residual longevity of the equipment. The case-based reasoning tool is presented by Boral et al. (2019) in a framework to detect, isolate and to suggest appropriate maintenance tasks for the large-scale complex machinery of a steel processing plant using the prior fault histories available. Finally, Fumagalli et al. (2019) presented a data driven tool (which integrates different technologies such as CPS) to provide fault diagnostics transforming raw data from the shop-floor into information, finally enabling risk-informed decision-making.

For what concerns the "supply chain" macro area, Pang et al., (2017) presented a dynamic intelligent scheduling system applied to a large steelmaking-refining-continuous casting production to adjust the schedule or generate a new executable schedule upon the occurrence of unanticipated disruptions and changes. Another solution for the rescheduling problem is described in Peng et al. (2018) with an Improved Artificial Bee Colony algorithm to replan for possible machine breakdown disruptions. A digital twin is presented in Liu et al. (2019) that can achieve production scheduling model dynamic development and self-maturation. To improve the productivity of the value chain, Valente et al. (2017) proposed an intelligent inventory tracking system using IoT and RFID to automate a warehouse. In 2018, Hatterscheid and Schlüter presented a decision support approach for selecting physical objects in collaborative supply chain processes for cyber physical system-transformation applied at a German steel producer.

Finally, the macro process most cited in the literature is that of "process control and optimization". In Han et al., (2019) a dynamic prediction model of carbon content and temperature value in molten steel at the later stage of steelmaking is constructed based on machine learning techniques; another predictive neural model for the reduction in steel temperature between the ladle and the caster considering the main sources of heat losses is presented in Duerte et al., (2020). Expert Systems are implemented by different papers for production control, for electric arc furnace optimization and pollution control (Costoiu et al, 2016), for early detection of undesired deviations and automatic definition of corrective actions improving blast furnace performance, fuel rates and operational stability (Bettinger et al., 2018). In Ananthapadmanaban and Karthik (2019), an Expert System is developed to identify the optimum input parameters, namely permeability, pouring temperature and green strength of the sand in order to give a lower probability of defects. In Beskardes et al (2019) this technology is used to adjust coke, limestone and dunite ratios automatically to achieve the desired Reduction Degradation Index value and predict the probability of occurrence of defects. A fuzzy rule-based Expert System is described in Vannocci et al. (2014) to control the charging gates of a sinter plant supporting operators in the control of the plant. In 2016, Byeong- Woo et al. proposed a framework integrating CPS and other technologies for smart manufacturing, in order to enhance ability of the analysis of shop floor data, providing a solution and taking autonomous measures to some extent; the CPS and IoT solutions are also implemented to monitor the production and calculate product assembly complexity and reuse data to retrieve similar past orders (Mourtzis et al., 2018). An online monitoring system based on an IoT system architecture is proposed for continuous steel casting production line by Zhang et al. (2016) integrating various data processing techniques including protocol conversion, data filtering, and data conversion.

9.1.3 Minerals sector

In general, the Minerals sector is strongly related with the mining industry, so the majority of references retrieved are related to the physical extraction process of minerals, the machinery involved, the processing/filtering of the raw material once extracted, and so on. There is also an important aspect of geological surveys for prospection and safety. The search of the AI&BD technologies in the minerals sector has identified the process which is most frequent, "(Model predictive) process control and optimization" with 15 references and the least frequent process as "product customization" with 1 reference.

Reviewing the processes in order, firstly for "Market trends and Open Innovation" we identified two papers: (Gokhberg et al., 2020) corresponds to the technology of "natural language processing" and whose objective is to identify technological developments as a "foresight activity" in Russia. The work applies text-mining techniques to subjective opinions gathered through expert workshops. The presented methodology helped to link the technologies to dominant professional discussions and to flag key trends. The second paper, (Andriamasinoro & Danino-Perraud, 2019) applies machine learning to assess mineral substance criticality in the French market, in the specific case of cobalt. This corresponds to two AI sub-categories, "machine learning" and "intelligent agents".

For the second process, "Product Customization", we found just one reference, (Qi et al., 2018) which deals with an intelligent modelling framework for mechanical properties of cemented paste backfill, which corresponds to the "machine learning" AI sub-category. This backfill has an important application in the minerals industry and optimizing the mechanical properties by tuning control parameters is a complex process. An intelligent modelling framework was proposed for the mechanical properties prediction using machine learning (ML) algorithms and a genetic algorithm (GA). A decision tree (DT), gradient boosting machine (GBM), and random forest (RF), were used and compared for the mechanical properties modelling while GA was used for the hyper-parameters tuning.

For the third process, "predictive maintenance" is a more "mainstream" topic for which more references can be found. We selected three representative references, (Karatzoglou, 2020) corresponding to the "object and spatial recognition" AI sub-category, (McCoy & Auret, 2020) which corresponds to the "machine learning" and "object and spatial recognition" AI sub-categories and (Boral et al, 2019) which corresponds to the "case-based reasoning" AI sub-category. (Karatzoglou, 2020) explains how thermal cameras are used to capture images which are passed to an image recognition process for defect identification in a mining installation. (McCoy & Auret, 2020) is a review paper which describes how data-based modelling and machine vision are applied to fault detection and diagnosis. (Boral et al, 2019), on the other hand, describes how a cased based reasoning approach has been implemented to support maintenance tasks for large-scale complex machinery (i.e. gearboxes of iron ore processing plant) in a simplified and structured manner by utilizing the prior fault histories.

The fourth process, "Supply chain management (re) configuring and scheduling" is one of the process categories with fewer references (just 3), (Shokri et al., 2020) and (Dauvergne, 2020) in AI sub-category "intelligent planning" and (Kshetri, 2019) in BD sub-category "data management". (Shokri et al., 2020) use an intelligent model based on the neural-fuzzy approach aiming at a desired decision-making and reducing the uncertainty in the strategic planning in mineral holdings. Here, the strategies are presented based on three logics, namely business, added value, and capital market. After extracting the primary indices, the final indices of the three logics are selected by consulting with the mineral holding experts. (Dauvergne, 2020), on the other hand, presents the hypothesis, or risk, that AI instead of promoting a green sustainable economy, may actually potentiate non-renewable resource extraction, giving example scenarios. Finally, (Kshetri, 2019) states the case for combining artificial intelligence and blockchain as a solution for data security, reliable transactions, large volume distributed data processing, automating repetitive tasks, with a focus on process industries.

Next is the "star" process, "(Model predictive) process control and optimization", which attracts the most references and where it appears is the main activity of AI and BD efforts in process industries in general and the mineral sector in particular. For this, as well as the more "academic" literature references, we have also chosen two industry on-line magazines which published two articles with many interesting and up-to-date real case studies: (Linca & Nanescu, 2020) and (Karatzoglou, 2020). (Linca & Nanescu, 2020) evaluate how artificial intelligence is changing the mining industry, with examples of companies with successful applications in "machine learning" and "cyber-physical systems". For example, *Goldspot Discoveries Inc*. uses artificial intelligence for improving mineral exploration, reducing the "chance" and stochastic elements, *Drone Deploy* uses drones and computer vision to understand better the environment and the terrain where exploitation is to begin, and *Renard*, a diamond mine in Quebec has developed a smart system for waste sorting and disposal. On the other hand, (Karatzoglou, 2020) considers "smart mining" and how artificial intelligence can benefit the mining industry, with examples of successful applications especially in "object and spatial recognition". For example, the use of thermal cameras, then image recognition for defect detection in mining installations as well as for heat loss analysis. Specific examples are: *ThoroughTec Simulation* which provides personnel tracking systems that support mining companies to optimize training interventions that best match individual worker needs. Example technologies used are wearable sensors to continuously monitor worker behaviour; and *Rio Tinto* who have developed a fleet of autonomous vehicles for use inside the mine. Other references cover a wider selection of AI and BD sub-categories. For example, (McCoy & Auret, 2019) for "object and spatial recognition", consider machine vision as a main application category and for "machine learning" consider data-based modelling, fault detection and diagnosis. (Ali et al., 2018), on the other hand, have implemented and evaluated five AI models with the objective of predicting ash and combustible recovery of coal, going through flotation. The following techniques were evaluated: random forest (RF), artificial neural networks (ANN), the adaptive neuro-fuzzy inference system (ANFIS), Mamdani fuzzy logic (MFL) and a hybrid neural fuzzy inference system (HyFIS). It was found that the Mamdani Fuzzy Logic (MFL) model gave the best performance. The authors stated that a scale-up would be necessary to make the step from the laboratory tests to real deployment. (Flores et al., 2020) describe an experience using artificial intelligence techniques, particularly random forest, to develop predictive models for copper recovery by leaching, using data accumulated over a period of 20 years, from an enterprise present in northern Chile. In the AI sub-category of "intelligent planning", (Chen et al, 2019) present a study of landslide susceptibility evaluation using novel ensembles of bivariate statistical-methods-based (evidential belief function (EBF), statistical index (SI), and weights of evidence (WoE)) kernel logistic regression machine learning classifiers. A landslide inventory comprising 222 landslides and 15 conditioning factors (slope angle, slope aspect, altitude, plan curvature, profile curvature, stream power index, sediment transport index, topographic wetness index, distance to rivers, distance to roads, distance to faults, NDVI, land use, lithology, and rainfall) was prepared as the spatial database. In the AI-sub-category of "expert systems", (Leiviskä, 2016) presents a system developed using expert knowledge and rule-based systems, applied to process control: closed-loop such as using fuzzy control, or for tuning conventional controllers, changing control strategies and adapting to varying operation conditions. To finalize the summary for process "(Model predictive) process control and optimization", we mention the reference of (Qi, 2020) in the in the BD sub-category of "computing and storage infrastructure" which provides a brief introduction to big data and BDM, and it discusses the challenges encountered by the mining industry to indicate the necessity of implementing big data. (Qi, 2020) proposes a global database project where big data would be used together with other technologies (i.e., automation), supported by government policies and following international standards.

Finally, moving to the process of "research and innovation management, planning and design", this category acts as a sort of "catch-all" for references which don't quite fit into the other five processes, and which could be characterized more as off-line studies rather than deployment, with a longer term vision. In the AI sub-category of "data understanding and characterization", (Gerassis, et al., 2019) use statistical methods for categorical data analysis (multiple correspondence analysis) and AI (Bayesian networks) to analyse a database of occupational mining accidents for Spain for the period 2004–2017 to identify the factors most associated with the occurrence of fatal and non-fatal accidents. The results obtained allow to shed light on the hidden patterns present in different work situations where accidents can have fatal consequences. For the AI sub-category of "machine learning", (Guo et al, 2019) developed an ANN model for estimating mining capital cost for open-pit mining projects with high accuracy. This was compared with other machine learning algorithms such as Random Forest, Support Vector Machine, and Classification and Regression trees. For "intelligent agents", (Zhang et al., 2020) developed a novel artificial intelligence model to estimate the capital cost of mining projects using deep neural network-based ant colony optimization algorithm. For big data, "data protection", (Ren et al., 2020) describe a data-sharing mechanism based on blockchain and provide implementation suggestions and technical key points. They indicate the advantages of the approach for data sharing while ensuring data quality and data protection. Finally, (Litvinenko, 2020) describes a vision of the impact of the global digital economy on the technological development of the worldwide mineral sector.

9.1.4 Non-ferrous metals sector

Firstly, relating to the process of "product customization/design" the AI and BD technologies were mainly implemented for the analysis of the characteristics of the materials. The use of multivariate analysis, sensor data fusion and machine learning approaches, suggested by Vitola et al. (2017), allows inspecting an aluminum structure subjected to temperature changes; on the other hand, the models derived from machine learning in Gomber et a. (2017) are included in a novel framework that addresses the objective identification of the atoms in the grain boundary regions of the aluminum. In Zedel et al. (2019), computational algorithms for automated image acquisition and processing were developed for automatically acquired micrographs, while contrast enhancing functions and geometrical operations are used to identify the particles during the aluminum melt process. In Lan et al. (2020), the orthogonal test method and data visualization were used in the experiment to observe the effect of multifactor composite action on copper slag and the optimum ratio copper slag to be deposited on the surface without treatment to reduce serious environmental problems.

In the case of the "process control and optimization" process, machine learning is used by Caiazzo and Caggiano (2018) to find the correlation between the laser metal deposition process parameters and the output geometrical parameters of the deposited metal on aluminum alloy plates or to calculate other production parameters as phonon density of states, entropy and melting temperature (Kruglov et al., 2017). A combination of the artificial neural network and an artificial bee colony algorithm was implemented for predicting blast-produced ground vibration in a copper mine (Taheri et al., 2017). For the analysis of aluminum electrolysis an Expert System is proposed in Li et al, (2020): this technology, combined with real-world control systems, makes it possible to perform the monitoring and diagnosis and emergency decision making for the tank condition promoting the information construction of the electrolytic aluminum enterprise as proposed in Sun et al., (2020). Moreover, Mulero et al, (2015) suggested an Expert System as a solution used at the initial stage of an automated inspection system, helpful to a human expert, to take a decision on whether the spraying parameters splats are appropriated. In Guo et al. (2017), a case-based reasoning system is presented, which retrieves similar cases in a production manufacturing process of aluminum electrolysis to improve the economy and objectivity of management. Related to the use of BD technologies, in Sarnovsk et al., (2018) a scalable analytical platform was designed to support the collection, storage and processing of data to connect to the existing environment in the plant and use the data gathered to build predictive functions to optimize the production processes. Another example is provided by Perzyk et al. (2019) with a data analytics system that aims at predicting the casting quality based on the production data. These data are used for optimizing process parameters to raise the products' quality as well as to improve the productivity.

There are fewer examples of AI and BD applications referring to the “supply chain”, “predictive maintenance” and “research and innovation” process areas. In order to measure energy consumption in factories that reveal in detail the use of energy at each industrial machine and the energy consumed to perform a particular industrial process, CPS and Iot solutions were installed for aluminum factory parts in the automotive supply chain (Del Campo et al., 2018). In Kolokas et al., (2020), machine learning models are developed for forecasting upcoming faults before their occurrence; the models would be useful for an industrial operator if executed in real time, based on online process data, since potential anomaly alerts raised by the model could enable predictive maintenance. Moreover, Penciuc et al., (2016) developed a platform used as a decision support system in the early product design phase; the tool can simulate the life cycle of a product (from material selection to production and recycling phases) and calculate its impact on the environment helping the sustainability assessment integration into product life cycle management. Finally, a machine learning model is proposed by Wen et al., (2019) to assist the design of high entropy alloys to optimize multi-component systems, such as bulk metallic glasses and superalloys, towards desired properties.

9.1.5 Engineering sector

The number of findings of publications on AI&BD technologies in the engineering sector vary depending on the topics. This occurs especially on the third level of the keywords. On the second level, more articles were found for specific concepts such as “Product customization” and “Predictive maintenance” rather than on the broader keywords e.g. “Market trends and open innovation” or “Research and innovation management, planning and design”.

Most publications were found for the two processes of product customization and predictive maintenance. For the process of product optimization, nearly all topics are addressed, however research appears to be concentrated more on Cyber-physical systems (CPS), where the cyber physical integration of processes enables an efficient production at a higher quality even for customized products (Runji et al. 2020). The product innovation process is supported by Expert Systems based on explicit knowledge (Waris et al. 2017). Also Natural Language processing is used to identify the needs of the customer from e-commerce websites (Wang et al. 2020).

In the area of predictive maintenance, CPS are used to minimize machine downtimes introducing intelligent operations (Meesublak et al. 2020), when adding agents, supervised factory-wide equipment maintenance is enabled (Chiu et al. 2017). On the other hand, Fuzzy Logic makes it possible to evaluate more complex failures (Alvares et al. 2019). Data required for the remaining life time of products can be estimated by different statistical models and machine learning technologies (Verhage 2020). To structure the input of BD for systems a four-layers big data architecture is proposed by (Salierno et al. 2020).

In the supply chain (re)configuring and scheduling process, AI&BD technologies are used for supply chain mapping of structures to increase their visibility (Wichmann et al. 2020) or generate a knowledge management for acquisitions (Almuiet et al. 2019). Addressing data protection, an integration of the Blockchain technology is proposed (Balasubramanyam, 2020). However, ML applications are still in an early development stage in the area of the supply chain process (Ni et al. 2019).

In the model predictive process control and optimization area, AI is applied in data management using digital twins based on machine data (Cheng et al. 2020) or taking it further creating an environment for optimizations in a real-time hybrid organization (Zhang et al. 2019).

For the process of market trends and open innovation, in the engineering sector only a few publications were found. In one example, machine learning is applied to short term stock movements and to identify market sentiment (Kalra et al. 2019).

The process of Research and innovation management, planning and design is the only topic in the engineering sector addressing data understanding and characterization. For example, (Klos 2016) considers using a knowledge management system in “engineer-to-order” organizations. In the context of machine learning, unsupervised learning was considered by (Usama et al. 2019) as well as security in the context of BD (Bagheri et al. 2015).

9.1.6 Chemicals sector

The search of the AI&BD technologies revealed a scarcity of literature in the application of AI&BD technologies in the “predictive maintenance” area as no papers were found when these level 2 keywords (see Table 1) were introduced in the search strings.

In the area of “Market trends and Open Innovation”, we included review papers and other studies that focused on identifying the trends of development and application of AI&BD technologies in the chemical sector. One of the retrieved papers focused on the machine learning technology application in artificial neural networks and related solutions (e.g. neuro-fuzzy) within different control loops such as network predictive control regarding energy savings (Kramer & Morgado-Dias, 2020). Most of the studies in the sample, focused on technologies related to Data understanding and characterization as main topics in which the research and development of AI&BD technology is focused. Some authors asserted that the digital transformation should still be considered the source of continuous effects of significant disruption, driving major opportunities for the development of the chemical sector (Piccione 2019), and others explored the challenges and opportunities of BD Analysis in Chemistry (Tetko et al. 2016). Other researchers analysed some technologies more in-depth when a specific trend of the R&D activities in the chemical sector was identified as growing. Examples of the latter case are the application of linear regression algorithms (LRA) and stochastic gradient descendent (SGD) in ML environments to predict a biomass higher heating value (Ighalo et al. 2020); or an original algorithmic analysis for environmental KPIs of chemical companies' efficiency of energy use and decrease in GHG emissions (Makarova et al. 2019).

Only a very limited amount of research was found related to "product customization" processes, where the only papers retrieved were related to the Machine Learning technologies applied to different industries in which chemicals processes are relevant, and applying artificial neural networks (ANN). We found a study of optimization-based ANN combined with extreme learning machine (ELM) algorithms implemented to classify damaged wheat grains together with an artificial bee colony (ABC) (Sabanci 2020); also a combination of ANN and genetic algorithms (GA) using AI approaches to improve modelling quality (Fernandez et al. 2017). The same considerations stand for the "Supply management (re)configuring and scheduling" process, in which only two studies were retrieved, focused respectively on the application of the technologies of machine learning and computing and storage infrastructure. The first study, applied ML for the electrification of chemical manufacturing (Blanco et al. 2019), while the second applied multi-sensor data-fusion algorithms using AI to reliably share data, plan the supply chain, execute purchase orders, deploying computing and storage infrastructure technology in the development of plastic waste circular economy (Chidepatil et al. 2020).

The research and innovation management, planning, and design processes resulted to be widely studied in the literature of AI&BD technologies application in the chemical sector. Scholars focused on the technologies for data understanding and characterization, applied to manufacturing 4.0 using advanced analytical platforms to develop predictive modelling approaches (Rendal & Reis, 2018); or deployed the technologies to benefit from real time data to prepare for the renewed focus on process reliability and safety in the chemical industry (Khare & Chin, 2017). Only one study applied machine learning technology to effective model and control fluidized bed reactors (FBR) for design, scale-up and simulation studies; the paper proposes an adaptive neuro-fuzzy inference system based on control performance indicators (Abbasi et al. 2019).

We retrieved several studies dealing with the application of BD technologies applied for data management and computing and storage infrastructures. Scholars studied the progress in data interoperability to support computational toxicology and chemical safety evaluation, exploring new approach methodologies (NAMs) in chemical safety evaluation to address the current public health implications of human environmental exposures to chemicals with limited or no data for assessment (Wratford et al. 2019). Other scholars developed the Experiment Specification, Capture and Laboratory Automation Technology (ESCALATE), a software pipeline for automated chemical experimentation and data management, that simplifies the initial data collection process, and its reporting and experiment generation mechanisms simplify ML integration (Pendleton et al. 2019).

Last, but not least, we retrieved studies on the application of BD for computing and storage infrastructure technologies in the research and innovation processes of the chemical industry. These technologies were applied in computational modelling methods and tools for formulated product industry (McDonagh et al. 2019), and for effective BD analysis to boost the use of enzymes for the transformation of a new array of renewable feedstock and enlarge bio catalysis scope (Pellis et al 2018).

9.1.7 Ceramics sector

A search of scientific literature of the AI&BD technologies in the ceramic sector according to the keywords previously identified was performed. The ceramic sector revealed scientific literature mainly centered on “process control and optimization” with a higher contribution in “machine learning” and “intelligent planning”. Less contribution was found for “product customization”, “research and innovation management, planning and design”, “supply chain management (re) configuring and scheduling” and “predictive maintenance”. No results were found for the area of “market trends and open innovation” when we introduced the keywords as search parameters.

The ceramic industry shows, on average, low levels of innovation, a low technological level of products, and resorts massively to artisan processes (Ruggieri et al. 2016). Production presents low efficiency, produces much waste and has a product defect rate higher than the average of other industries (Braccini & Margherita 2019).

Ceramics is an important engineering material. Material design with desired properties prior to manufacturing is crucial. Its characteristics, such as brittleness and hardness, present difficulties when it is being processed with high precision. Grinding is one of the methods to finish parts with high accuracy and is highly studied in literature. Quality control (defects detection and classification) and final material characterization with high precision are also key requirements and great effort is put into these aspects.

Research efforts are mainly focused on “process control and optimization”. Machine Learning is applied for quality control in the detection of defects using ANN based signal processing techniques in real time (Keshataju et al. 2014), as well as defects classification by combining the acoustic emission with ML techniques (Cunha et al. 2018) and using an unconventional ultrasound sensing approach with the application of ML for classification (Tripathi et al. 2019). ML techniques and Finite Element Methods (FEM) are also applied to evaluate and optimize Powder Bed Fusion (PBF) AM processes and parameters (Baturynska et al. 2018).

Intelligent Planning is also used for quality control in the manufacturing process by using ANNs where the addition of the reagent is controlled to optimize the final product (Kowalski & Rosienkiewicz 2017), trajectory planning of redundant manipulators in the grinding process (Diao et al 2017), real-time prediction of surface roughness deviations (Primenov et al. 2018) and a trajectory planning system solution for glazing spraying using cooperative multi-robots (Qian et al. 2020).

References of Expert Systems were found for different applications: for example, evaluating rotary ultrasonic machining to select optimum machining parameters (Sadegh Amalnik 2018), processing of ceramic- based materials with complex geometry using the main additive manufacturing (AM) technologies (Travitzky et al. 2014), and in combination with a multi-class support vector machine for defect detection and classification, with an automatic image processing system (RIMLV) (Hanzaei et al. 2017).

Technologies focused on Object and Spatial Recognition have been found in two papers: the first for the development of a new feature-based method for manufacturability analysis in AM by using a Heat Kernel Signature in the identification of geometric features and manufacturing constrains (Shi et al. 2018); and the second one dealing with the optimization of ceramic materials by additive manufacturing using 3D printing and photopolymerization (Eckel et al. 2016).

One study based using a Case Based Reasoning (CBR) approach was found, (Boral & Chakraborty 2016) developed a decision-making model for selecting the most appropriate NTM process for given work material and shape feature combination. Regarding Cyber-physical systems, a paper focused on the combination of “physics” with AI and machine learning to advance manufacturing design, processing, and inspection is reported (Aggour et al. 2019).

The greater part of works related to Big Data was found in "process control and optimization" technologies. For example, data visualization through mathematical algorithms to generate big data sets for the virtual image patterns of cracks on the surfaces of ceramic products (Park et al. 2019); data processing using convolutional neural networks (CNN) to detect defects and classify them using sensed images (computer vision) for a manufacturing process (Min et al. 2020); analysis of the development of the Internet of Things (IoT) and proposition of an Energy Efficiency Management System (EEMS) for building a ceramics production line (Wang et al. 2016); finally, a plan development application was found which uses a holistic approach to process and manage data, which was applied to support the analysis of multi-material jetting (CerAM MMJ)

A predictive maintenance reference was found applied to the ceramic grinding process, which considered the development of intelligent systems using machine learning (ANN) for the analysis of acoustic emissions and cutting power signals (Nakai et al. 2015).

The following are some examples of the literature focused on the "supply chain (re)configuring and scheduling" process: a framework of data-driven sustainable intelligent/smart manufacturing based on demand response, improved the energy efficiency of ball mills (Ma et al. 2020); the redesign of a physical factory layout through the interconnection of all the machines in a cyber-physical system, governed by a control information system, made it possible to keep track of the data produced and allowed the company to manage the production process in a flexible manner (Braccini & Margherita 2019).

Regarding product customization in the ceramic sector, literature was found on data- driven machine learning and design strategies for maximizing the energy storage density of ceramic materials (Yuan et al. 2019) and intelligent planning for the optimization of the experimental conditions to provide the maximum hardness of ceramic samples (Gayour et al. 2015).

Other applications found were: the identification of the factors affecting the hardness of ceramic samples - relation between the hardness and the process parameters - optimizing the experimental conditions to provide the maximum hardness. An AI based model provided a mathematical formula relating the hardness of the samples and the process parameters. Formula optimization and optimum values for achieving maximum hardness determination.

Finally, in "research and innovation management, planning and design", two papers in the area of Big Data were found. A study for the transformation of a ceramic manufacturing factory into smart ceramic manufacturing through IoT based big data analytics (Faisal & Katiyar 2016); the resulting generic framework was mapped (Faisal & Katiyar 2016). Scholars also studied a more efficient development of better functional materials through data analytics, revealing a clear path toward the enhanced use of data science technologies (De Guire et al. 2019).

9.1.8 Cement sector

For what concerns the "product customization/design" process, the papers mainly focus on the analysis of the mechanical and chemical characteristics of the cement product. For example, in Yaseen et al. (2018) a machine learning model is proposed to predict the compressive strength of foamed concrete, using as input parameters the cement content, oven dry density, water-to-binder ratio and foamed volume, whereas Marani and Nehdi (2020) used the compressive strength of cementitious composites; Gulbandilar and Kocak(2016) developed prediction models using Artificial Neural Networks and Adaptive Network-based Fuzzy Inference Systems for the flexural strength of the cement mortars. Moreover, DeRousseau et al., (2018) implemented a machine learning application to approximate the properties of concrete and consequently optimize the proportions of a mixture.

In the process area of “process control and optimization” several technologies were applied, in contrast to “product customization/design” which focused mainly on machine learning. For example, in Li et al. (2016) the working principle of the grate cooler system and the main factors that affects the efficiency of the system were analyzed through applying Expert Systems and a fuzzy control system to control and correct the speed and grate chamber pressure of the grate. Teja er al. (2016) developed a predictive model control and a fuzzy based real time optimizer to optimize a triple string calciner kiln considering factors such as the changing of raw material and various alternative fuels in burning that makes the process more complex and difficult to control. In addition, Ning et al., (2019) propose a case-based reasoning approach for setting the temperature value of a cement rotary kiln firing zone and to adjust it online according to the change of the relevant parameter value to meet the needs of clinker calcination. A similar approach is developed also in Zhou and Yuan (2014) including two digital filters to predict online the burning zone temperature over time, according to the measured secondary variables. The implementation of CPS and other digital technologies is tested in Jena et al. (2020) demonstrating that a self-organized system enables the factory to achieve higher efficiency, and minimize negative environmental impacts and improvements in other key performance indicators. Contreras et al. (2017) created a new software tool to improve the ability to interpret and diagnose critical job parameters while the system is in progress, and provide a contingency plan to avoid long waiting times, by performing a detailed post-job analysis of the raw acquisition data. The work proposed by Torres et al. (2017) aims to explain and demonstrate how the integration of cementing process real-time data acquisition and cement design can be used to monitor and control critical job parameters such as pressure behavior and equivalent circulating density. The combined data can be broadcast to any location and the operator is able to remotely follow the job execution.

Regarding the “predictive maintenance” process area an example of BD application is provided by Liu et al., (2015) in which a new Bayesian Network (considered a reliable method in data mining), can establish the fault diagnosis model of cement rotary kiln and realize a precise and rapid fault diagnosis. Whereas for the “supply chain” process area, Saffari et al. (2019) implement an Expert System to improve methods for the environmental impact assessment of a cement plant; the use of data visualization, data analytics, and statistical approaches is investigated in Egilmez et al, (2017) to identify the heavy carbon emitter industries and their percentage shares in the supply chains, for each layer and CO_2 source. Moreover, a web-based tool for developing strategies to sustainably manage resource and waste flows is proposed in Chen et al. (2017). The data visualization tool supports sustainable materials management, which is important in reducing environmental pressures and the demand for resource extraction and it is tested for the use of the cement made from blast furnace slag.

9.2 ANNEX - ROADMAPS

Find below the complete list of European roadmaps analyzed in Section 5.2.1

1. EFFRA: VISION FOR A MANUFACTURING PARTNERSHIP IN HORIZON EUROPE (2019)
    a. Sector: manufacturing
    b. Time horizon: 2021-2027
    c. Available at: https://www.effra.eu/sites/default/files/190312_effra_roadmapmanufacturingppp_eversion.pdf

- ManuFUTURE- SRIA FOR A COMPETITIVE, SUSTAINABLE AND RESILIENT EUROPEAN MANUFACTURING (2019)
    a. Sector: manufacturing
    b. Time horizon: 2030
    c. Available at: http://www.manufuture.org/wp-content/uploads/ManuFUTURE_SRIA_2030_Vfinal.pdf

- ARTEMIS: STRATEGIC RESEARCH AGENDA 2016
    a. Sector: ICT
    b. Time horizon: 2017- 2025
    c. Available at: http://ec.europa.eu/information_society/newsroom/image/document/2016-19/sra2016_15445.pdf

- Aeneas-Artemis-EPoSS: Electronic Components & Systems-Strategic Research Agenda (2019)
    a. Sector: ICT
    b. Time horizon: 2030
    c. Available at: https://www.ecsel.eu/sites/default/files/2019-02/ECS-SRA%202019%20FINAL.pdf

- Big data Value Association: BIG DATA CHALLENGES IN SMART MANUFACTURING - Discussion Paper on Big Data challenges for BDVA and EFFRA Research & Innovation road maps alignment (2020)
    a. Sector: ICT
    b. Time horizon: 2030
    c. Available at: https://ai-data-robotics-partnership.eu/wp-content/uploads/2020/09/AI-Data-Robotics-Partnership-SRIDA-V3.0.pdf

- ALICE: A framework and process for the development of a ROADMAP TOWARDS ZERO EMISSIONS LOGISTICS 2050 (2019)
    a. Sector: logistics
    b. Time horizon: 2050

   c. Available at: http://www.etp-logistics.eu/wp-content/uploads/2019/12/Alice-Zero-Emissions-Logistics-2050-Roadmap-WEB.pdf

- VERAM: Vision and roadmap for european raw materilas (2018)
   a. Sector: process industry
   b. Time horizon: 2050
   c. Available at: http://veram2050.eu/wp-content/uploads/2018/10/D5.2-RM-Research-Roadmap-and-recommendations.pdf

- SPIRE: SPIRE ROADMAP (2016)
   a. Sector: process industry
   b. Time horizon: 2020
   c. Available at: https://www.spire2030.eu/sites/default/files/pressoffice/spire-roadmap.pdf

- SPIRE 2050 Vision: A new Value Proposition for Horizon Europe and beyond
   a. Sector: Process industry
   b. Time horizon: 2050
   c. Available at: https://www.spire2030.eu/sites/default/files/users/user85/Vision_Document_V5_Pages_Online_0.pdf

- Processes4Planet (2020): Transforming the European Process Industry for a sustainable society
   a. Sector: process industry
   b. Time horizon: 2050
   c. Available at: https://ec.europa.eu/info/sites/info/files/research_and_innovation/funding/documents/ec_rtd_he-partnerships-industry-for-sustainable-society.pdf

The following table summarizes the research needs extracted from roadmaps

Roadmaps	**topic/call linked to AI and BD**	
EFFRA: VISION FOR A MANUFACTURING PARTNERSHIP IN HORIZON EUROPE	**Excellent, responsive and smart factories** Scalable first-time right manufacturing Agile and robust optimal manufacturing	**Parallel product and manufacturing engineering** Integrated end-to-end life-cycle engineering from product to production lines, factories and networks Concurrent, holistic and collaborative product-service engineering Manufacturing smart and complex products

	Low-environmental footprint, customer-driven value networks Demand and costumer-driven manufacturing networks Sustainable symbiotic manufacturing networks	**Human-driven innovation** Co-creation in European knowledge networks Human & technology complementarity Managing constant change
ManuFUTURE- SRIA FOR A COMPETITIVE, SUSTAINABLE AND RESILIENT EUROPEAN MANUFACTURING	**Processes and Technologies** Zero-defect strategies for small-batch manufacturing Systemic bio-inspired manufacturing platforms **Nano-technologies and materials** Multi-functional multi-material systems	**Digital transformation: DYNAMIC and FLEXIBILE production systems** Cyber physical systems of systems for dynamic production and logistics Integrating neurocognitive processes with AI in factories and value networks
	Digital transformation: QUALITY in production systems Cloud-based and edge-based cyber-physical systems for efficient in-line root-cause analysis in the manufacturing of complex high added-value products Machine / deep learning for autonomous quality in the smart factory Smart sensors systems for improving quality and use of resources	**Agile Manufacturing** Artificial intelligence (ai) enabled robotic systems for manufacturing Artificial intelligence at the shop floor Decision making tools for flexible assembly lines reconfiguration Adaptive and autonomous production control Manufacturing systems cognitive digital twins Learning processing machines for variable raw materials
	Robotics and Flexible automation Autonomic robots and flexible manufacturing systems Shared autonomy in manufacturing – cobots- cooperative manipulation Customer–driven manufacturing Factories of the future manufacturing the products of the future: collaborative platforms for value creation	**Human-Centred Manufacturing** Advanced behavioural and cognitive models for humans in manufacturing Behavioural and cognitive human-machine systems Augmented humans - unobtrusive assisting technologies for workplace support Analytics for data-human interaction Human-centric data and information models and tools

ARTEMIS: STRATEGIC RESEARCH AGENDA 2016	**Digital Platforms: Cyber-Physical creating smart services**: Cyber Physical System research should focus on building services in smart spaces based on the capabilities of CPS and promoting the interoperability of CPS as objects or nodes in Internet	**Design Methods, Tools, Virtual Engineering** increasing level of automation (up to autonomy) of Cyber-Physical Systems Elaborate decision-making capabilities and handling of uncertainty Techniques and tools for the optimisation of heterogeneous models with multiple objectives stemming from different application and engineering domains as well as across the supply chain
	autonomous and cooperative systems Safe and robust environmental perception of environment Learning and adaptive behaviour Advanced mobility and manipulation capabilities	**Computational blocks:** Move toward distributed systems More and more heterogeneity Autonomic systems
Aeneas-Artemis-EPoSS: Electronic Components & Systems-Strategic Research Agenda 2019	**Digital Industry** Developing digital twins, simulation models for the evaluation of industrial assets at all factory levels and over system or product life-cycles Implementing AI and machine learning to detect anomalies or similarities and to optimise parameters Generalising condition monitoring, to pre-damage warning on-line decision-making support and standardisation of communication scenarii to enable big data collection across huge (remote) sites Developing digital platforms, application development frameworks that integrate sensors/actuators and systems	**Health and Wellbeing** Developing platforms for wearables/implants, data analytics, artificial intelligence for precision medicine and personalised healthcare and wellbeing **Transport and smart mobility** Managing interaction between humans and vehicles

Big data Value Association: BIG DATA CHALLENGES IN SMART MANUFACTURING - Discussion Paper on Big Data challengesfor BDVA and EFFRA Research & Innovationroad maps alignment	**Skills and Knowledge** Work towards the alignment of curricula and training programmes for AI, Data and Robotics professionals with industry needs Development of complementary short-courses related to AI, Data and Robotics aimed at decision- makers in industry and public administration	**Experimentation and Deployment** Establish AI, Data and Robotics large scale demonstrators aligned to European industry needs Stimulate cooperation between all stakeholders in the AI, Data and Robotics value chain around experimentation and deployment
	Data for AI Create the conditions for the development of trusted European data sharing frameworks to enable new data value chain opportunities, building upon existing initiatives and investments Promote open datasets and new open benchmarks for AI algorithms, subject to quality validation from both software engineering and functional viewpoints Promote standardisation at European level but maintain collaboration with international initiatives for made-in-Europe AI to be adopted worldwide	**Systems, Methodologies, Hardware and Tools** Automated testing and soft validation of systems, including physical systems able to guarantee regulatory compliance Safety autonomous learning used in critical applications
	Action and Interaction: Complex collaborative interaction between multiple agents Complex social interaction in multi-actor environments Human environment reconfigured around interaction Safe interaction in dynamic and uncertain environments	**Knowledge and Learning:** Enable transparency by learning understandable models (open the black box) Effective applications of modelbased AI Support for human interrogation of AI decision making Development of intrinsically secure and privacy-preserving algorithm Reduction of the data demand for learning
	Reasoning and Decision Making Adaptive decision-making by incorporation of environmental changes Human-centric and compatible decisionmaking by incorporation of social interaction and mental models	**Sensing and Perception:** New materials and processing techniques will yield new forms of sensing and data acquisition; Self-configuring and adaptive sensors IoT supported by ubiquitous networks of AI-based sensors
ALICE: A framework and process for the development of a	**Fleets and assets are energy efficient**: Cleaner and efficient technologies Efficient vehicles and vessels	**Transport modes are smartly used and combined:**

ROADMAP TOWARDS ZERO EMISSIONS LOGISTICS 2050		Multi-modal optimisation Synchromodality
	Fleets and assets are shared and used to the max: Load optimisation Load consolidation and asset sharing Open warehouses and transport networks	**Freight transport demand growth is managed** Supply chain restructuring Decentralisation of production and stockholding
VERAM: Vision and roadmap for European raw materials	**Resource-efficient processing for raw materials**: allow raw materials input to be brought into a new era of customised manufacturing, imposed by environmentally-conscious customers and shifting market demands towards carbon neutral processes	**Raw materials in new products and applications** Increased automation and artificial intelligence will drive demand for ore technologies and with it more materials.
SPIRE ROADMAP 2016	**Feed** Optimal and integrated re-use of water	**Process** Process monitoring, control and optimization New energy and resource management concepts (including industrial symbiosis)
	Horizontal Methodologies and tools for crosssectorial Life Cycle and Cost Assessment as well as novel social Life Cycle Assessment of energy and resource efficiency solutions	**Waste2Resource** Systems approach: understanding the value of waste streams Value chain collection and interaction, reuse and recycle schemes and business models Technologies for (pre)treatment of process and waste streams (gaseous, liquids, solids) for re-use and recycling
SPIRE 2050 Vision: A new Value Proposition for Horizon Europe and beyond	**Digitalisation/Connecting the dots** A smart integration of process industries across Europe	**Industrial symbiosis**
	Energy efficiency Electrification of industrial processes Energy mix and use of hydrogen	**Resource efficiency** Capture and use of CO2/CO Resources flexibility
Processes4Planet (2020): Transforming the European Process Industry for a sustainable society	Digital materials design Digital process development and engineering Digital plant operation	Intelligent material and equipment monitoring Autonomous integrated supply chain management Digitalisation of industrial-urban symbiosis

9.3 ANNEX – EUROPEAN PROJECTS

ICT PROJECTS

Topic	Project	Macro-area	Technology
DT-ICT-03-2020	VOJEXT: Value Of Joint EXperimentation in digital Technologies for manufacturing and construction	Process control and optimization	Cyber-physical systems
ICT-01-2014	IMMORTAL: Integrated Modelling, Fault Management, Verification and Reliable Design Environment for Cyber-Physical Systems	Not specified	Cyber-physical systems
ICT-38-2020	AI-PROFICIENT: Artificial Intelligence for improved PROduction efFICIEncy, quality and maiNTenance	Process control and optimization	Machine learning
ICT-01-2019	CPSoSaware: Cross-layer cognitive optimization tools & methods for the lifecycle support of dependable CPSoS	Predictive maintenance	Cyber-physical systems
ICT-25-2016-2017	BADGER: RoBot for Autonomous unDerGround trenchless opERations, mapping and navigation	Process control and optimization	Object and spatial recognition
ICT-16-2015	Cloud-LSVA: Cloud Large Scale Video Analysis	Not specified	Machine learning
ICT-25-2016-2017	VERSATILE: Innovative robotic applications for highly reconfigurable production lines - VERSATILE	Product design	Object and spatial recognition
DT-ICT-11-2019	SYNERGY: Big Energy Data Value Creation within SYNergetic enERGY-as-a-service Applications through trusted multi-party data sharing over an AI big data analytics marketplace	Process control and optimization	Data management
ICT-09-2019-2020	ReconCycle: Self-reconfiguration of a robotic workcell for the recycling of electronic waste	Not specified	Object and spatial recognition
ICT-38-2020	knowlEdge: Towards AI powered manufacturing services, processes, and products in an edge-to-cloud-knowlEdge continuum for humans [in-the-loop]	Not specified	Data management and protection
ICT-01-2019	1-SWARM: Integrated development and operations management framework for cyber-physical systems of systems under the paradigm of swarm intelligence	Not specified	Cyber-physical systems
DT-ICT-11-2019	PLATOON: Digital PLAtform and analytic TOOls for eNergy	Supply chain management	Data processing

ICT-38-2020	MAS4AI: Multi-Agent Systems for Pervasive Artificial Intelligence for assisting Humans in Modular Production Environments	Process control and optimization	Machine learning
ICT-38-2020	ASSISTANT: leArning and robuSt deciSIon SupporT systems for agile mANufacTuring environments	Process control and optimization	Machine learning
ICT-38-2020	COALA: COgnitive Assisted agile manufacturing for a LAbor force supported by trustworthy Artificial Intelligence	Not specified	Intelligent agents
ICT-23-2014	SARAFun: Smart Assembly Robot with Advanced FUNctionalities	Process control and optimization	Cyber-physical systems
ICT-34-2016	SMART.MET: PCP for Water Smart Metering	Process control and optimization	Data processing
ICT-38-2020	STAR: Safe and Trusted Human Centric Artificial Intelligence in Future Manufacturing Lines	Process control and optimization	Machine learning
ICT-16-2015	PROTEUS: Scalable online machine learning for predictive analytics and real-time interactive visualization	Not specified	Machine learning
ICT-05-2019	MULTIPLE: Multimodal spectral sensors and orchestrated deep models for integrated process optimisation	Process control and optimization	Machine learning

FOF PROJECTS

Topic	Project	Macro-area	Technology
DT-FOF-11-2020	InterQ: Interlinked Process, Product and Data Quality framework for Zero-Defects Manufacturing	Process control and optimization	Machine learning
DT-FOF-04-2018	INTEGRADDE: Intelligent data-driven pipeline for the manufacturing of certified metal parts through Direct Energy Deposition processes	Process control and optimization Product design	Data processing
FOF-03-2016	STREAM-0D: Simulation in Real Time for Manufacturing with Zero Defects	Process control and optimization	Data processing
DT-FOF-11-2020	OPTIMAI: Optimizing Manufacturing Processes through Artificial Intelligence and Virtualization	Process control and optimization	Data protection
DT-FOF-02-2018	ROSSINI: RObot enhanced SenSing, INtelligence and actuation to Improve job quality in manufacturing	Process control and optimization	Cyber-physical systems
FOF-09-2017	SERENA: VerSatilE plug-and-play platform enabling remote pREdictive mainteNAnce	Predictive maintenance	Machine learning
FOF-09-2017	PreCoM: Predictive Cognitive Maintenance Decision Support System	Predictive maintenance	Machine learning

FoF-05-2014	DIVERSITY: Cloud Manufacturing and Social Software Based Context Sensitive Product-Service Engineering Environment for Globally Distributed Enterprise	Product design	Data management
FoF-01-2014	PREVIEW: PREdictiVe system to recommend Injection mold sEtup in Wireless sensor networks	Process control and optimization	Cyber-physical systems
FoF-01-2014	MAShES: Multimodal spectrAl control of laSer processing with cognitivE abilities	Process control and optimization	Machine learning
FOF-11-2016	ConnectedFactories: Industrial scenarios for connected factories	Not specified	Not specified
FoF-04-2014	SatisFactory: A collaborative and augmented-enabled ecosystem for increasing SATISfaction and working experience in smart FACTORY environments	Not specified	Not specified
DT-FOF-12-2019	MERGING: Manipulation Enhancement through Robotic Guidance and Intelligent Novel Grippers	Process control and optimization	Object and spatial recognition
FOF-09-2017	PROPHESY: Platform for rapid deployment of self-configuring and optimized predictive maintenance services	Predictive maintenance	Predictive maintenance
DT-FOF-02-2018	SHERLOCK: Seamless and safe human - centred robotic applications for novel collaborative workplaces	Process control and optimization	Object and spatial recognition
DT-FOF-02-2018	SHAREWORK: Safe and effective HumAn-Robot coopEration toWards a better cOmpetiveness on cuRrent automation lacK manufacturing processes.	Process control and optimization	Object and spatial recognition
DT-FOF-11-2020	DAT4.ZERO: Data Reliability and Digitally-enhanced Quality Management for Zero Defect Manufacturing in Smart Factories and Ecosystems	Process control and optimization	Predictive maintenance
FoF-08-2015	MC-SUITE: ICT Powered Machining Software Suite	Process control and optimization	Data management
FOF-13-2016	ENCOMPASS: ENgineering COMPASS	Process control and optimization	Data management
FoF-09-2015	BEinCPPS: Business Experiments in Cyber Physical Production Systems	Process control and optimization	Cyber-physical systems
FOF-11-2016	SAFIRE: Cloud-based Situational Analysis for Factories providing Real-time Reconfiguration Services	Supply chain management	Data processing
FoF-08-2015	MAYA: Multi-disciplinArY integrated simulAtion and forecasting tools, empowered by digital continuity and continuous real-world synchronization, towards reduced time to production and optimization	Supply chain management	Cyber-physical systems

FOF-02-2016	THOMAS: Mobile dual arm robotic workers with embedded cognition for hybrid and dynamically reconfigurable manufacturing systems	Supply chain management	Object and spatial recognition
DT-FOF-02-2018	CoLLaboratE: Co-production CeLL performing Human-Robot Collaborative AssEmbly	Process control and optimization	Object and spatial recognition
DT-FOF-12-2019	SOFTMANBOT: Advanced RoBOTic Technology for Handling SOFT Materials in MANufacturing Sectors	Process control and optimization	Object and spatial recognition
FOF-03-2016	GOOD MAN: aGent Oriented Zero Defect Multi-stage mANufacturing	Process control and optimization	Cyber-physical systems

SPIRE PROJECTS

Topic	Project	Macro-area	Technology
DT-SPIRE-06-2019	COGNIPLANT: COGNITIVE PLATFORM TO ENHANCE 360º PERFORMANCE AND SUSTAINABILITY OF THE EUROPEAN PROCESS INDUSTRY	Process control and optimization	Machine learning
SPIRE-01-2014	ProPAT: Robust and affordable process control technologies for improving standards and optimising industrial operations	Process control and optimization	Data understanding and characterization
DT-SPIRE-06-2019	INEVITABLE: Optimization and performance improving in metal industry by digital technologies	Process control and optimization	Case based reasoning
SPIRE-02-2016	FUDIPO: Future Directions of Production Planning and Optimized Energy- and Process Industries	Process control and optimization	Machine learning
DT-SPIRE-06-2019	COGNITWIN: COGNITIVE PLANTS THROUGH PROACTIVE SELF-LEARNING HYBRID DIGITAL TWINS	Predictive maintenance Process control and optimization	Machine learning
CE-SPIRE-10-2018	iCAREPLAST: Integrated Catalytic Recycling of Plastic Residues Into Added-Value Chemicals	Process control and optimization	Machine learning
DT-SPIRE-06-2019	FACTLOG: Energy-aware Factory Analytics for Process Industries	Process control and optimization	Machine learning
DT-SPIRE-11-2020	AI-CUBE: Artificial Intelligence and Big Data CSA for Process Industry Users, Business Development and Exploitation	Not specified	Not specified
DT-SPIRE-06-2019	HyperCOG: Hyperconnected Architecture for High Cognitive Production Plants	Process control and optimization	Cyber-physical systems

SPIRE-02-2016	COCOP: Coordinating Optimisation of Complex Industrial Processes.	Process control and optimization	Machine learning
DT-SPIRE-06-2019	CAPRI: Cognitive Automation Platform for European PRocess Industry digital transformation	Process control and optimization	Machine learning
SPIRE-06-2015	SHAREBOX: Secure Management Platform for Shared Process Resources	Supply chain management	Data processing