AI CUBE

[D1.2] SECTORIAL ANALYSIS OF INDUSTRIAL PROCESSES IN EUROPE

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6	added extra explanation in exec. summary
9	methodology, added extra explanation
36	added extra explanation to intro. of conclusions
37 - 40	added extra discussion regarding Table 5, (i) if technologies are sector specific and (ii) needs and challenges on a sector-by-sector basis. Also updated Table 5 column 3 in terms of needs and challenges.

Quality check review	
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Ron Weerdmeester, PNO	Overall Quality Review and Consistency Check
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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
WFI	Water For Injection
GVC	Global Value Chain
PPE	Personal Protective Equipment
EOL	end-of-life
HT	high-throughput

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1. EXECUTIVE SUMMARY

This report describes a sectorial analysis of industrial processes in Europe, which follows on from the first deliverable in which we presented an overview of AI and BD technologies and their application degree in the SPIRE process industries.

The following consists of a report of the sectorial analysis of industrial processes in Europe, which summarises the most relevant industrial processes per process industry sector in Europe, highlighting major challenges where AI and BD could play a relevant role.

In contrast with the first report, which was mainly obtained by a literature review, the present report also includes input from real projects and stakeholders, as well as input obtained from the first AI-CUBE stakeholder workshop held on 2nd February 2021 and from Industry information sites and content.

This document will provide input for the final Task 1.3 of WP1, as well as an adequate starting point for the definition of AI-CUBE framework for maturity and penetration level assessment in WP2, detailed mapping outlined in WP3, and the roadmap for process industry established in WP4.

Recall that in D1.1, the original CUBE (from the DoA), was evaluated in the Technologies dimension. Now in D1.2 we will review the Processes dimension (sector by sector), and the detailed findings of D1.1 and D1.2 will then be consolidated and summarized in D1.3 to produce the final cube.

Also, note that in D1.2 we focus more specifically on a review of the European Union as geographical area, with references taken from European projects and industrial companies, wherever possible. This is further supported by the presentations of projects from the first "stakeholder meeting" (see Annex) with all participants from the Eurozone.

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.

The approach and the aim of the activities carried out within Task1.2 consist of general review regarding the most relevant processes of the key industry sectors represented by SPIRE (i.e. cement, ceramics, chemicals, non-ferrous metals, minerals, steel and water). Process and product-oriented stages such as R&D, design and production will be addressed, but also marketing, sourcing and distribution will be taken into consideration. The review includes some information relating to the needs depending on company size/resources, however this will be expanded in upcoming project phases and deliverables. An initial shortlist will be generated, and in following deliverables and work packages this will be shared within the SPIRE community for complementary feedback, aiming at guaranteeing proper representativeness of process industry reality throughout Europe. The key focus of the deliverable is to identify the main processes per SPIRE sector, and highlighting major challenges of the sectors where AI and BD can play a relevant role.

Specific challenges related to each of these processes will also be taken into consideration in order to drive the subsequent analysis. Coming from the five “macro” areas predefined during the preparation stage, a shortlist of industrial tasks or activities which could benefit from the deployment of these technologies will be prepared. Also, a focus will be given to existing AI and BD applications in process industries nowadays and the leaders for each sector and company size, as well as other transversal applications coming from other sectors. Furthermore, by understanding the key processes for each sector and the corresponding issues involved, this will set the ground for subsequent deliverables and work packages to explore and identify bottlenecks and issues which affect the uptake of AI and BD strategies, which will continue through further stakeholder interviews and feedback.

As a complement to this first industrial analysis, an initial list of key industrial stakeholders will be identified through a focused analysis of the stakeholders aligned with the one already conducted under the T2.1 (see D2.1, Plan for stakeholder involvement), showing direct connection to the consortium companies and other relevant actors in the EU scenario. Moreover, possible stakeholders meeting events will be drafted to set the basis of the industrial consultation process to be developed in WP2.

4. METHODOLOGY AND APPROACH

AI-CUBE aims to map the state-of-play of AI and BD in different organisational core-processes, especially where AI and BD are (expected) to play a key role in the future, taking into consideration the macro-“process areas” in each of the eight SPIRE process industry sectors (e.g. RD&I, process control, SC management, predictive maintenance and product customisation and traceability).

This approach, which will underpin all actions of the AI-CUBE CSA, is visualised in Fig. 1, where the four dimensions are represented 1) AI & BD technologies (D.1.1.), 2) SPIRE sectors, 3) Organisational core-processes where AI & BD can make a difference (D1.2), and 4) AI & BD Maturity Levels.

Again, we note here that in D1.1, the Technologies dimension was evaluated (resulting in a reference taxonomy for the AI and BD technologies), and now in D1.2 we will review the Processes dimension (sector by sector). However, the CUBE is not updated until D1.3 when all the information (from D1.1 and D1.2) is consolidated and the new dimension categories are defined.

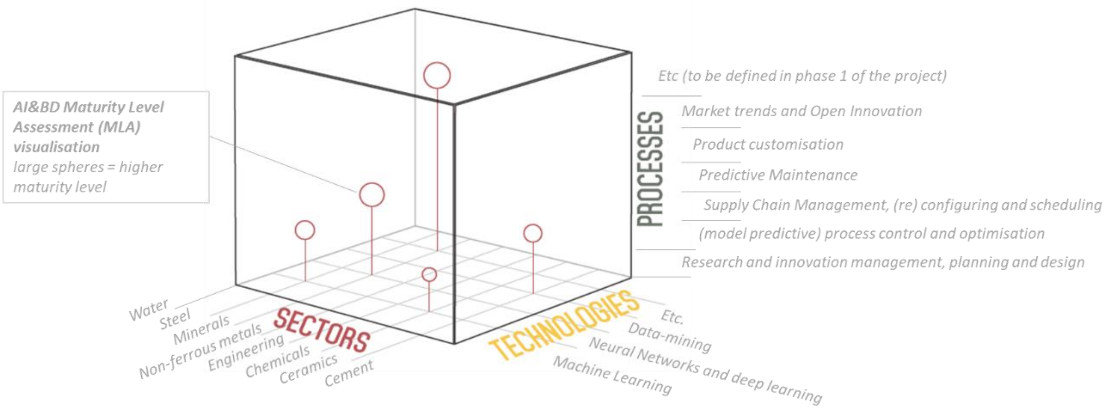

Figure 1. The original “cube” concept (from DoA)

In D1.1. we highlighted the key technologies and “heat-mapped” the macro-“process areas” where AI/BD focus is strongest in the different process industries. The current Deliverable D1.2. is complementing that by zooming in on the “processes” of the different process industry sectors, and highlighting the key-challenges these sectors have, where AI/BD can add value/ make a difference in the future.

In order to do so, we applied a methodology and systematic approach consisting of the following steps:

(i) Systematic review of **key processes of each SPIRE sector, their challenges and applicability of AI and BD as solutions**. Consideration is also given to the effect of the size/resources of the organization. In this way the project participants have gathered knowledge of the core business of each sector and the major processes involved in each industry, as well as the bottlenecks and problems for which digitalization in general and AI/BD may offer solutions.

(ii) Online Workshop organized and held in collaboration with stakeholders to obtain information and feedback with real stories and use cases, applying AI and BD in the

SPIRE sectors. In this way we also create a core group of stakeholders as a starting point for future work packages of the project.

This more in-depth information in key sector challenges, and to which macro-processes AI/BD may add value, provides insights in the current and future focus of AI and BD in different process industries (macro-areas) and their drivers. This will provide a basis for mapping maturity levels of these technologies, in the next phases of the project, in order to enable comparative analysis between states of development, transferability and RD&I needs towards future AI and BD business cases to be defined within the AI-CUBE project.

In the following chapters, we will hence highlight for each SPIRE sector:

- A summary of the key production and supply chain processes
- The key challenges the sector has to affront towards sustained or enhanced competitiveness
- Map per SPIRE sector, where in the key production and/or supply chain processes indicated in the "CUBE", AI/BD can add value to tackle these challenges (focus)

Once the focus of AI and BD use has been "cubed", future AI and BD driven business cases for the European process industries will be defined together with industry stakeholders, several of whom have already indicated support (see Letters of Support), and some additional ones have been identified in this Deliverable.

Eventually a gap analysis will be carried out to define required skills, data and RD&I within a set of roadmaps, targeting amongst others the key challenges per sector where AI/BD can make a difference, as outlined in this Deliverable.

5. REVIEW OF MOST RELEVANT PROCESSES OF THE SPIRE INDUSTRY SECTORS

In the following paragraphs we perform a review of the most relevant processes of the SPIRE industrial sectors. For each sector, in turn, we detail the key processes, and in each case the most relevant challenges and issues are identified, together with an analysis of the applicability of AI and BD technologies to improve the current functionality.

Before commencing with the sector by sector review, we present some transversal technologies with potential application to any field of processing [1]. Moreover, they are of possible relevance to many stages of the supply chain (Figure 2). Indeed, in some respects, they can transform the concept of a supply chain as distinct stages of economic activity. This is perhaps most obviously exemplified with Additive Manufacturing (AM) where, in practice, the production process becomes almost indistinguishable from design and logistics.

R&D	Design	Logistics (inward)	Production	Logistics (outward)	Marketing	Services
		Advanced industrial robotics				
		Industrial internet of things				
Additive manufacturing						

Figure 2 - Potential application of three game-changing technologies along the value chain [Source: Eurofound, The Future of Manufacturing in Europe – Game changing technologies].

The creation of 'digital twins' of all components in advanced process and manufacturing industries can minimise the risk of production stoppages and downtime due to accidental use of the wrong components in production processes. Forms of Industrial additive manufacturing (3D printing) have been effective in the 3D printing of both plastic and metal [2]. If Global Value Chains (GVCs) suffer from dislocation [3], as happened during the COVID-19 outbreak, and crucial components are unavailable from particular countries due to lockdowns and/ or temporary manufacturing closures, then having a digital inventory with digital twins could enable industry to source components from alternative suppliers.

There are also potential operational efficiency savings in different sectors. For example, in the **energy sector**, process improvements could result from the collection and analysis of data from sensors to provide predictive maintenance capabilities. In the area **of transportation and logistics**, there is scope to analyse bottlenecks in transportation across global value chains so as to identify potential improvements and to reduce transport costs [4].

In **critical infrastructures**, video surveillance systems are a key factor both for the internal security of the facilities and for the safety of workers. Due to the proliferation of tools to perfect and trains computer-vision solutions, it is also possible to propose solutions to monitor processes. This makes it possible to match images with other parameters coming from sensors, environmental data, etc., thus enabling more complete solutions for event detection. As example, a solution presented IoT Solutions World Congress (2018) which main idea was to automate the restricted access to different areas of the process, automatically detecting people and PPEs (Personal Protective Equipment), aiming to preventive security with a real-time record of prevention of occupational risks [5].

5.1 WATER SECTOR

The water sector's value chain links the environment and water resources to industries and utilities, the utilities to their customers, and both industries and customers back to the environment.

Utilities are complex organisations, with multiple activity areas and organisational layers, networks of data management systems, and disparate physical assets.

The supply chain of water and wastewater utility organisations always starts from water sources:

- Watershed;
- Surface, Groundwater and Water Reuse;
- Wastewater Effluent;

and typically involves processes like:

- Water Collection;
- Treatment;
- Distribution.

Water utilities and cities are now facing severe and demanding challenges. For example, losses due to natural disasters or dangerous human activities are mounting and on average cost governments over USD 300 billion globally each year [6].

The main challenges faced by the water industry can be summarised as follows:

- scarcer and less reliable water resources;
- severe weather patterns (e.g. floods and droughts or sea-level rise) make water less affordable, scarcer and with quality issues.

However, many more and disparate are the sources of concern and problems to tackle to have global societal impact, like e.g. groundwater depletion, untreated sewage discharges, water shortage and supply.

In order to become more resilient to the impacts of increasingly frequent, severe and hazardous challenges, the adoption of digital innovation, leveraging data and analytics, will be a necessary step. Water 4.0 could inform better system-level decisions and improve future outcomes for watershed management, operations, maintenance, capital planning and customer service [6].

The increasing complexity in the governance and management of water systems is indeed making room for the adoption of compelling transformative digital solutions (cloud, mobile, intelligent infrastructure, sensors, communication networks, and analytics and BD). For example, remote sensing and digital twin technologies deliver connectivity between utilities and their diversified water supplies. Multiple digital technologies can then provide connectivity within a utility's operations. Customer service and customer analytics tools are then able to bridge the gap between a utility and its clients, and open data platforms and citizen science projects can provide connectivity from the customer back to their water supply [6].

AI, BD and related enabling technologies will allow new and more effective system configurations, where surface water, groundwater and stormwater are mixed as potential sources; AI-enabled solutions are applied to separate waste by source (intelligent waste water treatment by source) and implementation of reclamation schemes (wastewater recycling, nutrient and energy recovery schemes); and mixed land-use promotes cascading water uses so to improve resource efficiency and limit unsustainable pressure on natural resources [6].

As reported by Kalanithy Vairavamoorthy, Executive Director of the International Water Association, the uptake of digital technologies and integration into water services will allow to tackle challenges offering smart solutions [6]:

- **Smart by design**: adaptive 'off-grid', distributed systems that provide diversity, and modularity, characteristics critical for resiliency;
- **Smart Use**: combining concepts of water fit for purpose (different grades for different uses), and resource recovery and reuse (of water, energy, and nutrients from wastewater);
- **Smart (Digital) Control**: IoT supporting data-driven models that can help integrate and optimise smart pumps, valves, sensors and actuators, and enabling each device to "talk" to each other, or for that matter to a customer's smartphone, and send real-time information to be accessed and shared via the cloud.

Emerging smart city initiatives on their turn will foster digitalisation across industries.

Industry uses water for multiple applications, each one with its own technical requirements and quality specifications. Used water, on its turn, needs treatment to make it fit for new uses or for disposal in a way compliant with environmental regulations.

An industrial water treatment system mainly treats water in view of one of the following purposes:

- consumption;
- manufacturing;
- disposal.

Usual industrial water treatment systems commonly include (see also figures below):

- Raw water treatment systems;
- Cooling tower treatment;
- Boiler feed water systems;
- Wastewater treatment systems.

Figure 3- Wastewater treatment plant

Pre-treatment and optimization of the source water are typical processes in the raw water treatment systems.

Suspended/colloidal elements, iron, microorganisms and hardness are usually removed during raw water treatment. Often, raw water treatment is aimed at protecting downstream machines and tools from scaling, fouling, corrosion, and other damages or precocious wear due to elements contaminating the source water [7,8,9].

Removing harmful impurities (e.g. dissolved or suspended solids, inorganic matter, biological materials, sulfates) prior to entering the boiler or cooling towers, and controlling the acidity and conductivity of the water are critical processes in boiler feed water, circulation water, blowdown water and cooling tower water treatment systems.

Industrial waste streams need then to be reused or disposed of by releasing them into the environment abiding by compliance regulations.

Key processes of the wastewater treatment are clarification (removal of suspended solids, both mineral and organic, from the raw water), disinfection (reduction of the bacteria, virus and protozoa populations), softening (removal of calcium, magnesium, and certain other metal cations) and distribution [7,8,9].

Industrial water treatment faces several major challenges [10], such as:

- The need for steady reassessment of contaminants and for a comprehensive chemical and toxicological analysis;
- Reducing the environmental footprint, mainly due to the disposal of the organic matter stripped from the wastewater;
- Reducing energy consumption, as filtering wastewater is an incredibly energy demanding endeavor;
- The need for new tools to empower workers to always make the best decisions in real time.

AI-enabled solutions have much to offer to the water industry in order to tackle the above challenges [11]:

- AI-driven solutions can leverage data analysis to produce more effective water treatment processes;
- Automation and innovation have a critical role to play to make wastewater management leaner, less energy intensive, more sustainable and more easily predictable and controlled;
- Predictive maintenance, high-resolution remote sensing techniques, smart information and communication technologies can generate improvements not only in the detection of harmful microorganisms, but also in water-use efficiency;
- AI can play a pivotal role in the management of water resources also in connection with water utilities;
- Data driven decision making would allow for immediate control and prevention of hazardous situations, whenever possible.
- Use of AI and BD to anticipate/manage the impact of climate change (draughts and flooding). The use of weather predictions in combination with water management systems is also relevant here.
- Use of AI /BD for managing the governance of the full water cycle, including all stakeholders from Cities to industries and agriculture, predicting/planning the trade-off of water availability (different “qualities” of water to be used fit-for-purpose) in interdependent circular water systems for all types of users.

The introduction of a large number of (cheap) sensors throughout the capillary water distribution network on society will open-up new opportunities to analyse, plan and manage water distribution in a complex system (similar to AI/BD based supply chain management Decision Support systems, in other sectors).

This concept of distributed sensors network, combined with apps used by citizens, will enable new business models (e.g. based on the actual use of different qualities of water, in combination with incentives → this will feedback into the AI-enabled scenario planning solutions).

Experts from process industry, industry 4.0 and industrial water management believe that water management, beyond moving towards digital new approaches, should also become more flexible and integrated in industrial production, municipal and water resources management [7,12,13].

In Figure 4, courtesy of [12], shows how horizontal integration (with industries, municipalities and water resource managers) and information integration, implemented within a properly orchestrated control and regulation system, are of essence for a successful future deployment of 4.0 practices in the water industry.

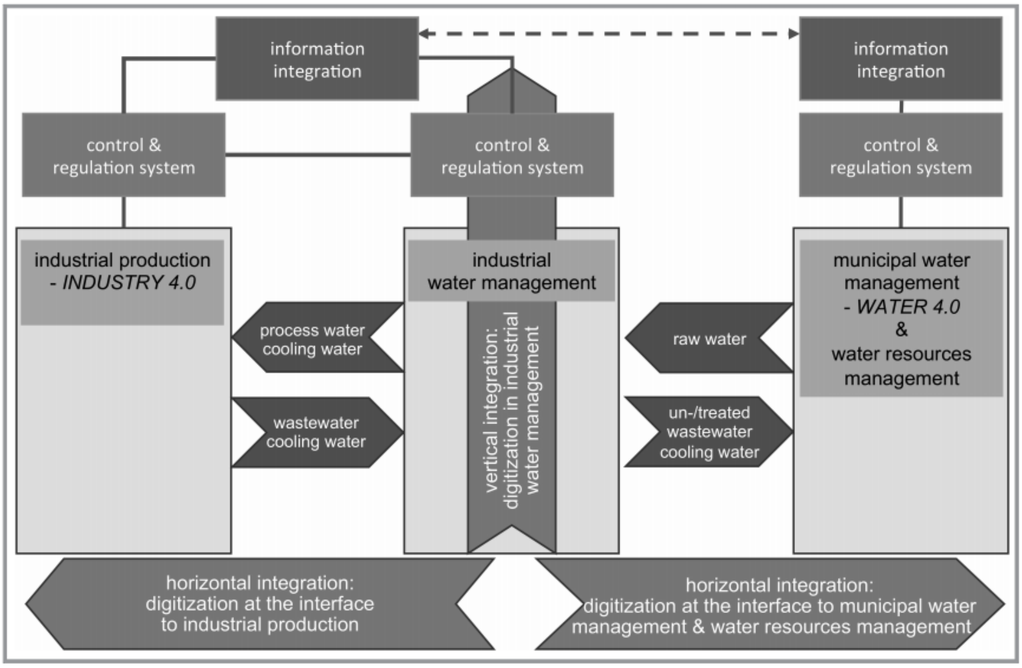

Figure 4 – Integration of processes, systems and competencies in the water industry

5.2 STEEL SECTOR

Around 29% of the total crude steel worldwide is produced by the electric furnace, compared to the 71% for iron-based production route [14]. High amount of fossil fuel consumption by coal use in iron-based steel production arise environmental concerns. Scrap-based production, compared to iron-based, consumes less energy (74%) and water (40%). In addition, it produces less pollution (76%) and environmental emissions (86%) [15]. Also, there is high amount of CO_2 emission in iron-based steel production, which accounts for ten times more than scrap-based production. By 2050 the availability of scrap will be almost doubled, deriving majorly from obsolete scrap [16]. Consequently, it is expected that global scrap-based steel production will increase from 520 million tons in 2018 to 733 million tons in 2030. Therefore, the demand for scrap will increase from 708 million tons in 2018 to 1,067 million tons in 2030 [15].

Therefore, new production processes foster the European electric steel producers in the transition towards a ‘recycling society’. The main pathways of this transition are smart carbon usage and carbon direct avoidance [17]. The benefits of using these solutions are less CO_2 emission, efficiency in the fossil fuel consumption, and less consumption of materials such as nickel, chrome, iron, and silica. Scrap and slag are the two crucial materials in steel production inbound and outbound flows, respectively, facilitating the steel value chain in a circular economy.

Among the six key components identified by the Sustainable Process Industry through Resource and Energy Efficiency (SPIRE), based on the 2030 vision of the research and innovation roadmap process industry [18], slag facilitates the valorisation and smarter use of feedstock (feed), and causes the avoidance and re-use of waste streams through the context of closed-loop value chains (waste2Resource). Among the strategic objectives set out by the European Steel Technology Platform [19], there is a particular focus on scrap and ferrous slag as the primary critical material in steel circular economy. It addresses the ferrous slag analysis as a new trend which can maximise the valorisation of the steel by-products in a local economy.

Therefore, we shortly describe the electric arc furnace (EAF) process. The main raw material is steel scrap and other inputs are pig iron and fluxes (Figure 5). Fluxes are used to remove the impurities in EAF and majorly are lime and dolomite. These raw materials are melted in the furnace using electric energy. Since scrap comes in different quality classes, quality control of the EAF liquid steel is required to pass the desired quality level to assure the correct melting. Low quality classes can cause the increase of pollutant elements in the slag formed in EAF, namely black slag.

To produce high-quality steel, the liquid steel produced by EAF is used in secondary metallurgy (ladle furnace-LF). In LF, like EAF, fluxes such as lime and dolomite are added. With the addition of alloys, steel is desulfurized, and high-quality steel is produced by means of electric energy and argon gas in LF. Second quality control is carried out in this phase. The liquid steel is then refined and goes through continuous casting for the production of billets, blooms, and slabs. In the final stage of rolling, high-quality steel products are produced.

The fluxes used in EAF and LF are chemically combined with the melted steel and form the slag on top of the furnace. The slag derived by EAF and LF production is chemically and physically different. EAF slag (black slag) is formed as black stony material after cooling, while LF slag (white slag) is typically formed as white powder material after cooling. Black slag is usually left in an open area to be cooled down. Water spray and air cooling are the additional activities which can facilitate the cooling phase. Black slag then undergoes physical treatments of crushing so that the desired grain sizes for different applications are obtained. Due to the presence of lime in WS, it can be directly applied as feedstock in EAF. White slag treatment is still under study and innovative technologies are under development.

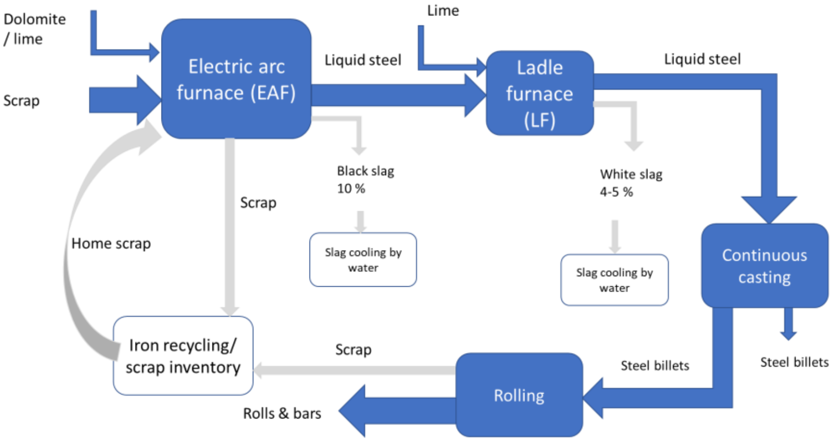

Figure 5 - Steel production process

The role of AI and BD in the steel sector can be summarised as follows:

- *Production process*: steel production process can expose workers to dangerous working conditions. AI can support the real-time integrated control of the different production phases enabling cyber-physical systems by new way to formalize and treat BD collected along the process from machines, devices etc.

- *Energy consumption*: the utilisation of AI algorithms can assure flexibility in production. Innovative systems can help to smooth the energy consumption along the period by suggesting ways to reduce it in the peak periods, maximising the renewable energies, minimising the generation costs, and reprogramming the consumption profiles.
- *Raw material quality control*: in case of EAF, the scraps arriving to the plant can be classified with a high precision and timely manner thanks to advance sensing systems and AI algorithms. Furthermore, these systems can detect the classified scrap in the inventory and provide a real-time monitoring of the inventory level for supporting production planning.
- *Raw material handling*: Intelligent robots enabled with AI can facilitate the scrap loading and transferring from the warehouse to the furnace avoiding human interaction in highly dangerous environments.
- *Monitoring and planning*: through automated in-house and external systems (such as GPS and laser sensors), the availability and timing of the materials can be tracked in real-time. The in-house monitoring consists the inventory level, position of the raw material and resources (e.g. internal transport modes) in the warehouse, operators' guide for timely picking and loading activities. Consequently, higher security for the employees is achieved in the workplace. The external monitoring consists of the real-time tracking of transport modes in the inbound and outbound flows.
- *Disruption prevention in decision-support solutions*: the process and supply chain of steel production encounter vulnerabilities due to several factors, such as suppliers delays and production disruptions. The current optimisation algorithms mainly focus on a single machine or a part of the supply chain. An integrated decision-support tool based on the optimisation of the whole value chain would be based on BD collected from different sources (machines, trucks, suppliers, warehouse) and can support event-management, and optimisation of the operations.
- *Market analysis and forecasting*: an online marketplace facilitates both the administrative and operative procedure to ensure a high-level collaboration with the other stakeholders in the value chain. An intelligent system for customer relationships management (CRM) and online monitoring and order management systems for the suppliers are among the prominent aspects in this criterion.
- *Value chain integration for circular economy*: an intelligent system that not only facilitates the forward flows of the raw materials and primary products, but also manages and integrates it with the reverse flows to the factory, waste management systems, and other value-added activities. To this end, it is critical to have the capacity to manage and analyse a huge amount of data.

5.3 MINERALS SECTOR

According to [20] which details the mining process, firstly the type of mining operation has to be established, for example, open pit or underground. To define the ore from the waste rock, samples are taken and assayed. The main processes for mining are: crushing, transport, grinding and sizing, leaching and adsorption, elution and electrowinning, bullion production and water treatment.

[21] details the key stages in the mining process: the first step is the prospecting/surveying. Skilled mine workers who can judge the quality of the lode are much sought after. This is followed by reaching the ore; breaking the ore underground; bringing the ore to the surface; dressing the ore; smelting the ore.

According to [22], a key aspect is the type of mineral, which determines how it is extracted and how it is post-processed. For example, coal, diamonds, iron ore, gold, etc. and whether the extraction is surface or underground. This results in different issues, challenges and required processes.

In [23], a major European service company dedicated to the mining industry gives details of what type of services they offer, which forms a useful list of the typical activities and processes which are performed in the mining industry and mineral processing. This includes, grinding mill upgrades, cone crusher, railcar dumper system, shutdown planning and scheduling, research and testing, repair/rebuild, process training, process feasibility, remote condition monitoring, corrective maintenance, condition monitoring, remote troubleshooting, process evaluations, preventative maintenance, mill reline, online monitoring, health and safety.

In [24] an evaluation is given of the challenges and opportunities for the mining industry in the future. According to the authors, key issues include: (i) the safeguarding of known resources; (ii) high-quality (scientifically and technologically driven) exploration surveys; (iii) improvements in mining and mineral transformation/ beneficiation; (iv) advances in consistent combinations of primary and secondary sources of raw materials, along with higher concerns on their judicious use; (v) effective and stable mining policies.

On the other hand, [25] evaluates process control challenges and opportunities in mineral processing. The authors discuss the significance of different phases and states: solids $\rightarrow$ water $\rightarrow$ air creating foam and froth. It is stated that all fluids are non-Newtonian, and the mineral content can double in a matter of minutes, changing the flow characteristics dramatically. The processes are complex, with many circulating loads. Another key aspect is with respect to planning, of setting realistic targets. For example, in the grinding stage, an operator has a number of parameters that can be evaluated in real time which provide an indication of how the mill is performing. As a baseline, ore hardness is quoted as the amount of power required to grind a mass of ore from one size to another, expressed in kilowatts per ton.

Another key aspect is the operational side: when there is a problem, the natural response of the operator is to cut back on the feed. However, this can result in a high loss of production if there are continual problems, as well as an increase in the amount of off-spec product due to poor particle size control, and the amount of energy used for grinding and recirculation of recycled material rather than for fresh feed.

It is stated that success requires an extensive and focused onsite study with communication and flexible technology. The plant's feed, equipment, special operational practices and culture must be understood, and changes made as needed to both. One systematic approach to this, is to develop on-site a definition of best practices. This requires working closely with operators over a period of time to see how operations change, based on problems and staff. Two key roles which provide know-how and synergy are the metallurgist and the controls engineer.

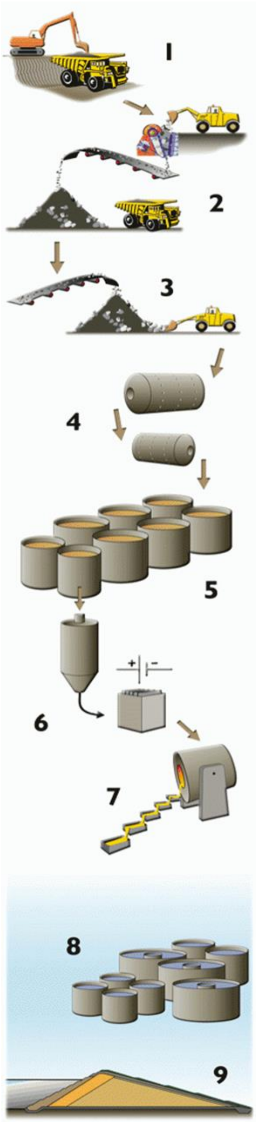

Figure 6 - Mining operations steps for extraction and processing

A survey of technological trends is given in [26] for the contemporary mining industry. Five main areas are defined: (i) Spatial data visualisation. This is considered a disruptive technology; (ii) Geographic information systems; (iii) Artificial intelligence; (iv) Automated drones; (v) Use of renewable energy by the Mining Industry.

In the case of AI, it is cited as now taking a lead in decision-making for knowledge based companies. They use smart data and machine learning to improve operational efficiency, mine safety, and production workflow. It is stated that implementing artificial intelligence technology generates day-to-day data in half the time than what has been used previously in the field. Also, the mining industry evolves rapidly, so machine learning and AI impact the way mines today make choices for the future. The following are indicated as some ways the latest technology in artificial intelligence impacts the working mine:

Mineral processing and exploration: companies can find minerals more easily by using high-performance AI technology.

Autonomous vehicles and drillers: over the past decade, mining companies have been incorporating autonomous vehicles in their pit-to-pit operations. Self-driving trucks can easily navigate through narrow tunnels with AI (SLAM technology). Now, drilling systems are also simplified with a single operator that controls several drill rigs at once.

Figure 7 - Autonomous vehicles used in mining operations

The overall objective is to obtain an optimal industry efficiency. As the mining industry attempts to reduce costs and lessen its environmental impact, techniques such as AI can help to ensure safety and reliability for both miners and the land that mines use.

Finally, in [27], different transformation technologies are discussed for the mining industry. They especially highlight: internet of things, robotics, plasma (to increase yields), 3d imaging technologies, automated drilling, remote operations control & monitoring.

5.4 NON-FERROUS METALS

Non-ferrous metals' annual production amounts to 47 million tons, with more than 900 plants across Europe. Its annual turnover is €120 billion in Europe, consisting of 77% in fabrication and transformation, 21% in refineries, and 2% in mining sectors [28]. Their direct job creation amounts to 500,000, and around 2 million, indirectly. Non-ferrous metals represent 20% of the world market. The EU's core sectors include batteries (11%), construction (24%), durables (5%), industry (20%), packaging (11%), and transport (29%) [29].

Non-ferrous metals have a high potential of recyclability, thus making them at the forefront of the circular economy. While 82% of the worldwide production is through the primary route, this share in the EU amounts to 50%, representing the EU's aim towards a circular Europe. 90% of the scraps are recycled from buildings, 90% from transport, and 60% from packaging [29]. Thus, almost half of the base metals in the EU are produced through the secondary route, with a potential increase of 50% by 2050. The overall GHG emissions from their production process have reduced by 60% since 1990, and a reduction of 81% is foreseen for 2050 [30]. Compared to other manufacturing sectors, non-ferrous metals production is the most energy-intensive process, accounting for 58% share among the other energy consumed throughout the process. Therefore, optimising production through AI and BD will significantly affect the energy efficiency, climate protection, and resource efficiency.

Aluminium and copper are the most predominant base metals produced in Europe. Their production is estimated to increase in the coming decades due to the higher availability of scrap. In particular, Aluminium scrap will increase from 4.5 million tons to 9 million tons in 2050 and copper scrap will be almost doubled from 1.6 million tons currently available [30].

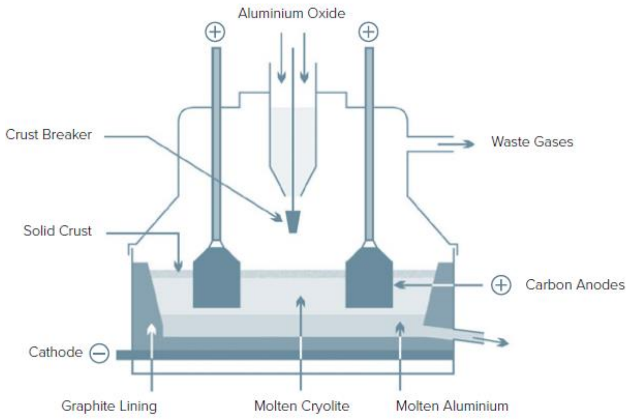

Figure 8 - Primary production of aluminium from alumina [30]

The aluminium primary production process, as the youngest and largest sector, consists of two main stages, namely alumina (aluminium oxide) production from bauxite and aluminium production from alumina. Each ton of bauxite produces 20-25 tons of aluminium. The bauxite can be extracted from the mines in the EU or imported from outside the EU. In the first stage, known as the Bayer process, the bauxite undergoes the grinding, digestion (through heating by caustic soda), and precipitation phases. The alumina is gained after removing the impurities (such as iron) in the form of red mud and calcination (of around 1000 °C) of the purified proportion. In the second stage, alumina is inserted into the electrolysis cell (also known as pot) for electrolytic reduction. Alumina in the pot is combined with sodium aluminium fluoride (cryolite) at a temperature of approximately 960 °C provided by electric energy.

The raw material from the secondary production process can be either the new scrap generated from the wrought and cast production, or old scrap, from the end-of-life (EoL) products. This process not only fosters circularity in the production but also its energy consumption is much less than the primary production. The main process consists of melting the scrap in the furnace. The furnace type depends on the characteristics of the scrap. Some examples are the induction, rotary arc, and plasma furnace.

The pyro-metallurgical production route consists of 80% of copper production. The process phases include concentration to matte smelting, converting, fire-refining, electrolytic refining, and melting and casting. In the matte smelting phase, concentrates are first dried to lose around 7-8% moisture content. The drying can be carried out through either hot gas rotary driers or steam-heated coil dryers. The dried concentrate is then smelted and roasted in a furnace to reduce the ores' impurity contents. Iron silicates account for a high proportion of these solid impurities. The product of this phase is a mixture of copper sulphide and iron sulphide, known as matte. Depending on the impurities content, partial roasting may be carried out. There are two smelting processes, namely bath and flash smelting. The difference between the two is primarily due to the degree of oxygen enrichment. Flash smelting uses a lower degree of oxygen enrichment than bath smelting. In the second phase, matte is converted to blister copper (consisting of 98.5% copper) through one of the two methods of batch or continuous process. These processes oxidise the copper sulphide by oxygen.

For further purification of blister copper, it goes through fire-refining, where air and fluxing elements (such as hydrocarbons and ammonia) result in an oxidisation reactivity. This process is carried out in an Anode furnace. The final refining is performed by an electrolytic cell, consisting of a cast copper anode and a cathode that contains copper sulphate and sulphuric acid. Copper cathodes produced are then transferred to the melting and casting phase to produce the final product. The secondary production method follows the same processes as the pyro-metallurgical process.

AI and BD have a profound impact on the aforementioned processes to reduce energy consumption. Therefore, new IoT solutions are required not only to measure the energy consumption for a single machine but also measure the energy consumed throughout the production process [31]. Furthermore, an automated system for unifying the scrap quality classes prevents the additional processes and results in higher energy consumption for refining phases.

Unlike ferrous metals, the wide variety of product mixes and production processes in the non-ferrous sector results in unique AI solutions for each plant. Therefore, the role of the plant's production historical data is more dominant than the domain knowledge. This complexity emphasises the decision-support systems through machine learning techniques such as case-based reasoning [32]. However, the uncertainty and randomness in the knowledge and experience should not be overlooked [33]. Also, the adaptability of AI solutions highly depends on the collaboration of managers, engineers, and workers in a production plant. This complexity in the production process is also evident in the raw materials, where just a low proportion of them are the ores, and a high proportion consists of fluxes and other materials from different sources. Thus, the integration of the actors in the raw material provision from the suppliers to the plant requires timely and precise solutions. This aspect emphasises the role of decision-support systems in inbound logistics.

5.5 ENGINEERING

In this analysis, we assumed Engineering sector as the Engineering process concept applied to any industrial process including the SPIRE sectors. Engineering a process starts with the design of a solution followed by its implementation in an industry or its construction. This extends into every area of engineering types. Here are the main steps to take in the engineering process design and its implementation:

Table 1 - Engineering process design and implementation

PROCESS	ACTIONS	INDICATORS
Problem definition	Ask the customer Needs and Constraints Identification opportunities and requirements	Information
Research	Current solutions in the market Adaptable technologies Different specialists	Feasibility study
Identification/creation of solutions	Brainstorming Conceptualization	Develop as many solutions as possible
Choose a Promising Solution	Revisit earlier steps Comparison	Benefits
Test solution	Create and Build a Prototype Testing and analysis Solution redesign	Effectiveness (data collection and analysis) Advantages and disadvantages
Process implementation	Build the solution Industrial deployment Process integration	Operationalization (parameters) Optimization (adjustment) Information collection
Analysis and improvement	Process feedback Iteration	Sensors, data collection Data analysis

AI-powered technologies can help deliver more efficient designs than previously achievable by eliminating waste in the design process. Innovation can be brought to the market faster as AI facilitates lower process cycle times and an increased focus on real-time negotiations and other interactions. Lead times to market can be accelerated through the use of Virtual and Augmented Reality, whose adoption rates are expected to increase significantly [34].

The optimization of an engineering process can be improved with AI. Using data from Information Technology (IT) and Operational Technology (OT) sources, and insights from the company's process engineers, the production line of a **Chemical industry** [35] was modelled and a specific process-based data schema developed. Once modelled, supervised ML was used on real-time data to identify five primary root causes suspected of contributing to the high formation of side products. Then a predictive simulation was conducted to analyse different scenarios and determine the optimal operational conditions.

The implementation of the AI engineering solutions in the process and manufacturing industries brings two main advantages: i) an effective and accurate information processing, and ii) a powerful data storage and calculation. AI technology builds production model through computer simulation system and makes comprehensive data analysis to make relevant precautious measures in case of emergency, which guarantees the orderly production system, reduces the possible capital loss of manufacturing enterprises, and also greatly improves the production efficiency and accuracy of manufacturing. Applications of artificial intelligence in manufacturing and process industries [36]:

- Fault diagnosis. AI can automatically classify and categorize information to improve the accuracy of calculation, avoiding errors or failures and diagnosing.
- Quality inspection. Based on deep learning machine vision technology, AI detection makes quality inspection standards more unified, stable, and faster detection.
- Safer working places. AI recognizes the safety status of working places and warns the workers in case of emergency, set up visiting limitations of workers (image recognition), assess whether the workers on the spot are conforming to the safety regulations.
- In product development. AI (due to its powerful data storage and effective information processing) can help its clients find their desirable products and thus shorten the time for products design.
- In products manufacturing procedure, AI can help bring about most accurate products.
- In products rear service, AI provide far-distance equipment maintenance, spare parts management, routine or predictive equipment maintenance, fault warning and diagnosis, products upgrading, and etc.

Regarding the adoption according to the **company size**, independently of sectors, large companies tend to invest in AI faster at scale [37]. This is typical of digital adoption, in which, for instance, small and midsized businesses have typically lagged behind in their decision to invest in new technologies.

5.6 CHEMICALS SECTOR

The core activity of the chemical industry is the production of materials (e.g. plastics or coatings) for further processing in other industries. Here, different processes are used for the conversion of the materials, such as heating, mixing, grinding and cooling. Particular challenges in the chemical industry are process monitoring and the supply and disposal of the main and by-products, as process safety and ecological aspects are taking on an increasingly present role in society.

The term “green chemistry” has become increasingly important in recent decades and aims to make chemistry more sustainable in laboratories and industry. Already in 1998, Paul Anastas and the chemist John Warner developed twelve principles of green chemistry.

- waste avoidance
- atomic efficiency
- safer chemical transformations
- development of safer substances
- safer chemical solvents
- energy efficiency
- renewable resources
- reduce derivatives
- use catalysts
- naturally degradable
- real-time monitoring of waste disposal
- basic risk avoidance

These principles aim on the one hand to maximise resource efficiency and thus material, energy and economic efficiency, and on the other hand to eliminate or at least minimise hazards and waste. [38] In addition, the guidelines confront the industry with technical and process challenges where established methods are reaching their limits.

Since 2011, the number of employees in the chemical and pharmaceutical industry has been growing significantly. In this context, the proportion of highly qualified workers has also recorded a slight but continuous upward trend. Since 2008, there has also been a significant increase in sales in both industries. [39] In 2018, the chemical and pharmaceutical industry accounts for more than 10% of the share of sales in manufacturing. [40]

Besides, the share of both industries in terms of spending on innovation is above the average for manufacturing.[39] The increase in highly qualified workers, as well as the high spending on innovation, can be placed in a direct connection with the growing importance of artificial intelligence in the chemical and pharmaceutical industry in the future.

Important areas for the application of AI methods in chemistry are research and development, production, logistics and product tracking, and maintenance. Computer systems are being trained with big databases and are helping chemists and employees along the entire supply chain to make decisions at the individual company levels with different focuses.

Figure 9 shows the correspondence of the core processes of the chemical industry to the individual company levels. t the first two levels, “Enterprise management level” and “Production management level”, artificial intelligence plays a role primarily in the area of logistics, for example concerning enterprise resource planning in direct connection with production planning. Here, the focus is particularly on the processes of uninterrupted production supply due to continuous production in the chemical industry. Forward-looking planning and forecasting have a significant influence on process quality here. In addition, the topic of handling by-products is becoming increasingly important, as ecological and economic goals play a role in this area. This circular economy presents the chemical industry with further process-related challenges in the future

While at the two lower levels (Fig. 9), “Process control level” and “Field level”, the functions of artificial intelligence are designed more for direct process monitoring through control systems and process analyser technology.

A high degree of process reliability is required in order to be able to manufacture efficiently and safely. Continuous sensor-based monitoring of chemical process steps is a core aspect of the industry. Due to the increasing complexity and variety of products, the existing plants are more and more pushed to their limits. In this context, optimization of porosity is necessary with regard to the control of the variety of products and an adaptive planning of the aggregate occupancy. In addition, the chemical industry collects a large amount of sensor data from the respective plants, which is not yet used comprehensively for process optimization. There is great potential for maintenance planning and optimized plant occupancy in this field.

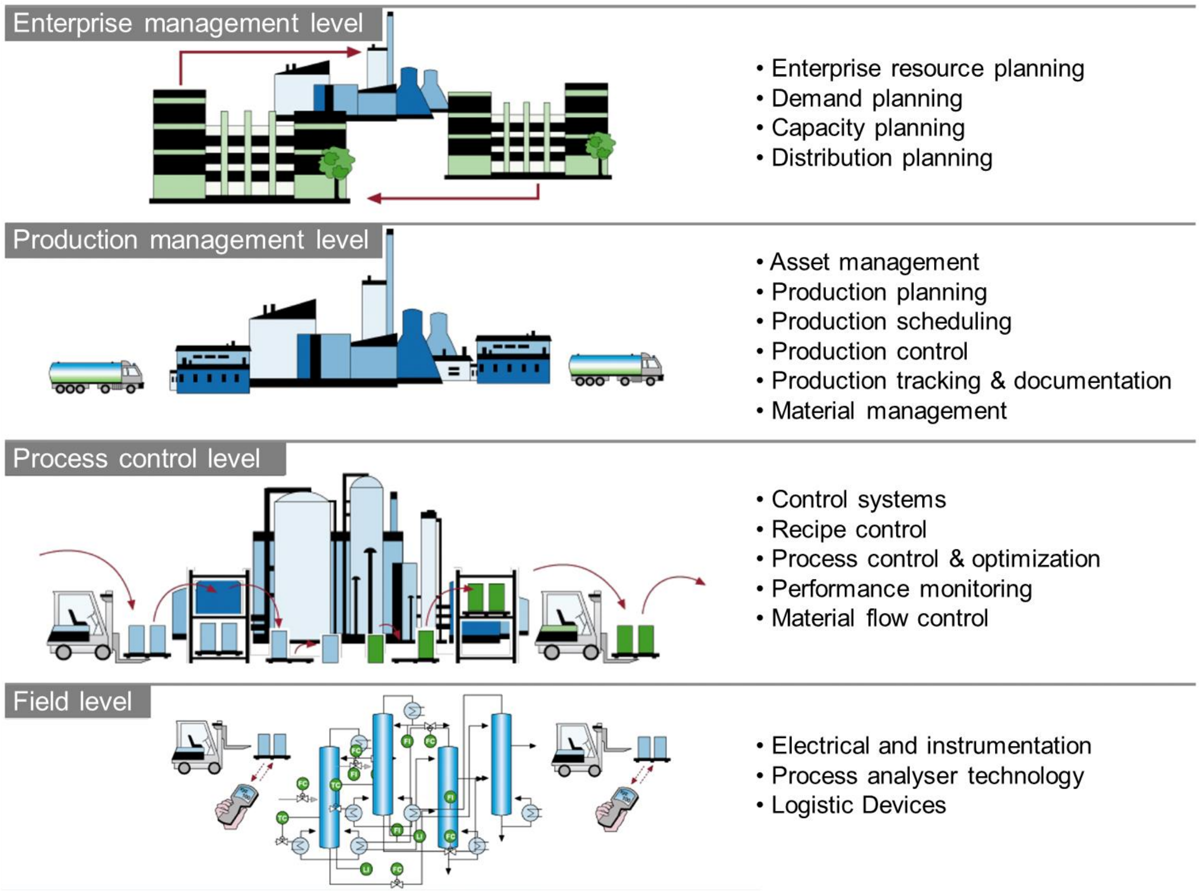

Figure 9 - Correspondence of the core processes of the chemical industry to the individual company levels. [9]

Especially in the area of chemical logistics, a large field of application for artificial intelligence is developing. Real-time tracking of dangerous goods shipments, collaborative planning processes along the supply chain, and automated cargo management all require the use of AI components. The German chemical and pharmaceutical company Merck relies on intelligent supply chains in this context. Intending to have enough products in stock to satisfy the existing demand on the market without product bottlenecks, the company uses the “Self Driving Operations” system. The program is fed with both internal information such as stock levels and production data as well as global information such as economic data or weather data. This enables the software to predict how demand will develop depending on external influencing factors and worldwide. An example of this would be the emergence of a flu epidemic. [39]

Another important component in the chemical industry at the "Production management level" is product tracking. AI components enable extensive product traceability and preventive intervention in processes to improve the efficiency and profitability of a company. Here, the first applications are available that allow products to be tracked worldwide and the data obtained to be structured and analysed across the board with the help of artificial intelligence. Important data sources here are social media, scientific literature or direct information from patients and doctors regarding reports of side effects of medicinal products. [39]

In addition to the large area of logistics, artificial intelligence is also increasingly being used in production at the "Process control level" and "Field level" to optimise processes sustainably. The area of process control and monitoring, in particular, is being expanded by intelligent cluster algorithms to ensure that the increasing demands of the market and continued economic production are satisfied. In connection with process monitoring, the maintenance and continuous improvement of safety play an overriding role concerning both the process and the plant. When converting modular plants, for example, artificial intelligence can take over time-consuming decision-making processes regarding plant safety and thus prevent long downtimes.

But not only are existing processes being further optimised with the help of artificial intelligence, but chemists are also being increasingly supported in research. The approach of using artificial intelligence to plan synthesis routes is already 60 years old. The problem, however, is that it is not enough to give the computer a large number of rules, because the complexity of chemistry cannot be logically grasped with simple rules. Especially retrosynthesis as a standard method for the production of chemical compounds is defined by an enormous complexity. For the production of a target molecule starting from its basic materials, there are numerous variants for each synthesis step that need to be compared and evaluated. Besides, for the efficient use of artificial intelligence, the available data must always be up to date, which is why the software has to independently learn the rules and applications from the constantly growing literature via deep neural networks. A research team led by the organic chemist Segler at the University of Münster has succeeded in achieving results that are 30 times faster with the help of artificial intelligence in retrosynthesis. [41]

Other notable examples of the use of artificial intelligence in the chemical and pharmaceutical industry include the "supercomputer" Quriosity from BASF in the area of research and the use of predictive maintenance in the area of maintenance and repair from Evonik Industries. Even if the areas of application and thus the requirements for the programs differ, it is clear in all areas that artificial intelligence does not replace experts but supports them concerning the collection and structuring of data to make sustainable decisions. [39]

The core aspects of AI and BD in the chemical industry are summarised in Table 2.

Table 2 – Summary of AI and BD in the chemical industry

Business Level	AI/BD technologies
Enterprise management level	▪ AI-based forecast ▪ Collaborative data exchange along the supply chain
Production management level	▪ Automated loading point management ▪ AI-based process monitoring (pattern recognition)
Process control level	▪ Predictive maintenance ▪ Real-time based product tracking
Field level	▪ Sensor-based quality monitoring (including R&D)

5.6.1 Focus on the Bio-Based Industry

The chemical industry, and in particular the green chemistry, is currently converging with industrial biotechnology [42] [43]. The connection between the chemical sectors and the bio-based one calls for a dedicated focus. Data show that the overall EU bio-based production accounts for about 4.7 Mt of bio-based chemicals per year, representing 3% of the total market for the 10 key chemical products. [44]. The EC assessed that the bio-based products and biofuels representing about € 57 B in annual revenue and 300 K jobs, would have risen to 12.3% of all chemical sales in 2015 and 22% by 2020, with a compounded annual growth rate of about 20%. [45] The Bio-based Industry Joint Undertaking Strategic Research and Innovation Agenda [46] set as a goal the development of new biorefining technologies that would enable the sustainable transformation of natural resources in bio-based products and materials.

Indeed, among the objectives of the EU bio-based industry for 2030 there is the enabling of 30% of the chemical production becoming bio-based, pursuing the goal of a more sustainable industry and the reduction of the GHG emissions to which the Chemical industry heavily contributes. Indeed, the proportion of industry that could become bio-based grows to over 50% when considering high added value chemicals and polymers [44].

The enhancement of the bio-based industrial production is tightly linked to the scale-up of manufacturing capabilities, diversification of processing technologies and cost reduction, i.e. the optimization of efficient biorefineries. Developing efficient biorefineries comparable to petroleum refineries allows the production not only of biobased product competitive with their fossil-based equivalents, but also the possibility of generating products currently manufactured by petroleum refineries, but also additional ones. [47]

While the bio-based industry can be considered under the chemical sector, as for processes and industry characteristics one specific phase in the upstream of the value chains assumes relevance: the supply section and the pre-treatment processes applied to convert raw material into biobased products. Indeed, those will apply a combination of different technologies based on thermal, mechanical, chemical, and biological processes. The biobased products in general result from secondary materials, however dedicated crops also exist for bio-chemicals or bio-fuel production. This implies that the feedstocks used as raw material for by-products must presents some specific requirements such as not only conveniency of prices, but also good quality, and reliable quantity and availability. In addition, specific individual skills and training are required for an effective product of biorefining. The main challenges arising for biobased products relate to the cost of the biobased raw material, and the development of new and/or better low-cost processing technologies converting raw material into biobased products.

Research showed that digital technologies can contribute to future R&D improvements in the bioprocesses, and particularly through the development of [47]:

- **new process monitoring methodologies**, thanks to microfabricated discrete sensors, real-time monitoring and digital imaging;
- **new process control concepts**, applying expert systems, artificial intelligence, neural networks, and principal component analysis.

Against the lack of data traditionally experienced in the biology experimentation, the XXI century witnessed astonishing technological improvements that made great quantity of data available in biology, generating the need for specific tools that could facilitate the analysis and interpretation of those data. In this context, predictive design and rapid evaluation are at the core of the bio-based approaches, along with the assembly of new materials through laboratory automation, high-throughput (HT) characterisation and post-production processing.

More in general, there are several processes in which the digital technologies can add value and improve the bio-based industry in particular, and in general any chemical or process industry (Figure 10). Some examples are given in [48]:

- Smart Design for extended products' life and improved recyclability
- Monitoring Systems based on automatic data flows for trend assessing, renewed production processes, emission calculation
- Stock exchange platforms for bio-based materials, digital marketplaces to increase bio-based materials availability, volumes, and improve quality assessment
- Advanced just-in-time delivery processes based on IoT or M2M communication for optimised delivery
- Decentralised production through 3D printing, enabling smaller modular manufacturing facilities, using Small Scale Intelligent Manufacturing Systems (SIIMS)
- Digital chains to connect supply chains across sectors based on horizontal and vertical integration through digital networks
- Consumer-centric and improved end-of-life usage through ingredient tracking
- Advanced computer-aided growth processes for growth processes' steering and tracking (e.g. input factors such as fertilizers, light, water)
- Augmented Reality (AR) training tools in human-machine collaboration
- Smart manufacturing enabling automatic control and steering of biochemical processes and communication across production entities

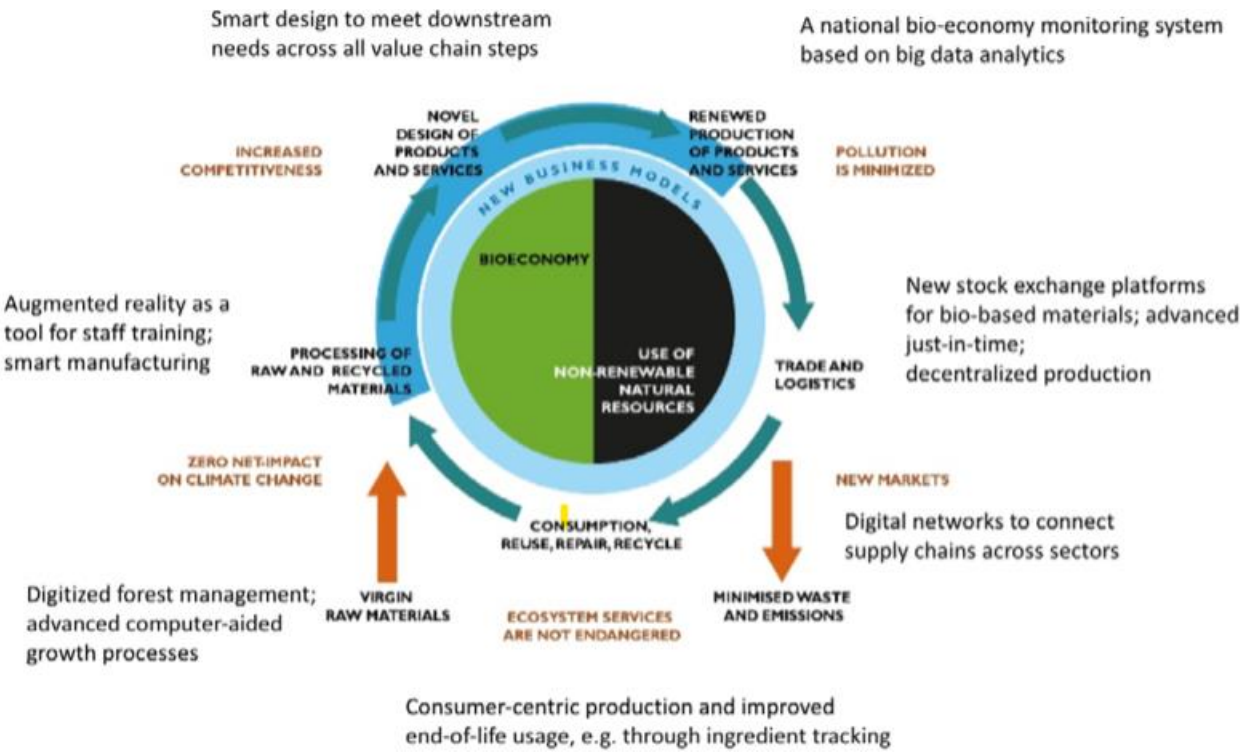

Figure 10 - Examples of digital accelerators for a circular and sustainable bioeconomy. Source [48]

5.7 CERAMICS SECTOR

The term ceramics comprises a much wider range of materials, including metallic oxides, nitrides and carbides. These materials are used in application areas from household items to high-performance tools for industrial use. In addition to their great hardness, ceramics are also resistant to thermal and chemical influence, making them highly suitable for applications where the product is subjected to high mechanical or thermal stress.

Ceramic forming methods include throwing, slip casting, tape-casting, freeze-casting, injection molding, dry pressing, hot isostatic pressing (HIP) and others. Methods for forming ceramic powders into complex shapes are desirable in many areas of technology. Such methods are required for producing advanced, high-temperature structural parts such as heat engine components and turbines.

Ceramic industry is divided in nine sub-sectors according to A.SPIRE: floor and wall tiles, bricks and roof tiles, refractories, technical ceramics, table and ornamental ware, sanitary ware, expanded clay, clay pipes and porcelain enamel. Other classifications also distinguish abrasives. Depending on the nature of the ceramic ware, typical process steps have to be followed in the target of specific size, shape and properties, as illustrated in Figure 11.

- Raw material collection, crushing and grinding (more of a manual method)
- Mixing (dry and wet)
- Forming (giving a specific shape, either manually or with a wooden mold)
- Surface coating with some design
- Drying to reduce the moisture
- Firing (to harden the shape and make it unbreakable)
- Machining and finishing (as if required)

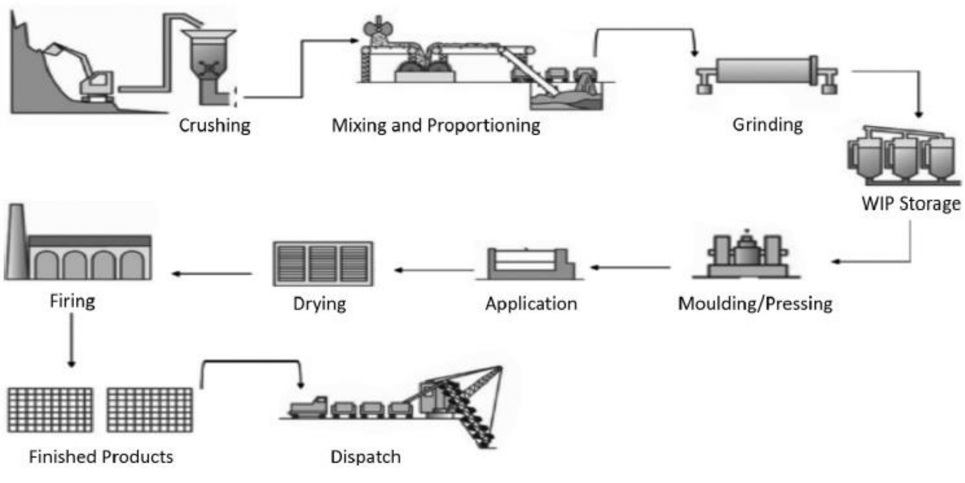

Figure 11 - Common ceramic ware processing protocol [49]

According to the processes in the ceramics manufacturing, different processes, activities and indicators have been identified to determine critical steps and improvement opportunities.

Three main problems may occur during the manufacturing: deformation, cracking and foaming. The deformation of the product is the most common and serious defect in the ceramic industry, such as the diameter of the cylinder is not round, and the geometric shape has irregular changes. The main reasons are improper kiln-drying method, quick temperature changes and excessively high firing temperatures. The reason for cracks on the product surface is that the preheating temperature rises too fast and then the cooling process occurs immediately, resulting in uneven shrinkage inside and outside the product. The bubbles on the product surface is mainly caused by the insufficient oxidation of the decomposition in the porcelain tire and the glaze as well as the content of sulphate and organic impurities in the billet glaze. These three problems comprise the principal quality control issues about ceramics.

Ceramic industry is energy intensive, namely due to the drying and firing processes, which involve firing temperatures between 800 and 2000 ºC. The manufacture of ceramic products is a complex interaction of raw-materials, technological processes, people, and economic investments. It includes the transport and storage of raw materials, ancillary materials and additives, preparation of raw materials, shaping, drying, surface treatment, firing, and subsequent treatment [50]. Complexity of the production process is diverse and also the market requirements are different for each ceramic industry sector. The main problematics found in the ceramic industry include according to the production process are:

- The company type of **production system** in force determines the flow of materials and semi-finished products during production orders. The production system is determined by the firing process taking place in roller or tunnel kilns. The continuous production system forces the planners responsible for production to the appropriate prior preparation of the batch.
- **Labor market – employee market** causes problems with employing people possessing appropriate qualifications. The skills that people working in ceramic plants possess, are an essential element of the company's operations.
- The **assortment and the degree of modernization** of the company. Producers of ceramic products compete with one another, offering their clients a modern, often changing design (changes in design and shape introduced several times a year). A wide and dynamically changing assortment in relation to a limited number of machines and devices results in a situation in which managers must carry out production based on inventory.
- Ceramic factories producing ceramic fancy goods or building ceramics are exposed to **fluctuations** in the sale of products due to seasonality. The barrier associated with the **continuous maintenance** of production affects the storage of inventory. Losses caused by overproduction or shortage of products are an obstacle in eliminating wastage.

Nowadays the ceramics industry is undergoing one of the most important changes in recent history. Ceramic manufacturing processes are highly automated from the point of view of product handling and material processing. However, one of the most common problems in the traditional ceramic sector is that the machines and equipment responsible for each manufacturing phase are not interconnected, therefore limiting the overall efficiency of equipment (OEE).

Align with this need, digital transformation based on AI&BD technologies allows to streamline decision making and connect all elements of the production chain more efficiently. The digitalization process in the ceramic industry faces different barriers

Table 3 - Main processes, activities and Key Performance Indicators (KPIs) in ceramics industry. Source: [49] and [51]

PROCESS	ACTIVITIES	INDICATORS
Raw materials	Transport	Transport within the plant
	Storage	Storage conditions (level indicators, overload valves and filters or gas displacement units)
		Stock control
Materials preparation	First size reduction	Size control
	Preliminary homogenisation	Homogenisation degree
	Weathering/Drying	Water content
	Crushing/grinding	Size control
	Classification	Homogenisation degree
Component mixing (dry and wet)	Proportioning of the mix components	Automated (computer control of the feeder mechanisms)
	Mixing	Degree of mixing (mixing time, intensity and sequence)
Shaping/forming of ware	Pressing/extrusion/ moulding/casting	Quality control
Drying	Drying optimization	Optimization (speed, thermal efficiency and low wastage)
	Drying process	Control (heating rates, air circulation, temperature and humidity)
Surface treatment and decoration	Texturing and facing	Process control
	Decorating techniques	Design, ink application
Firing	Firing control	Firing conditions (temperature, time)
	Final material control	Final properties control (mechanical strength, abrasion resistance, dimensional stability, resistance to water and chemicals, and fire resistance)
Machining and finishing	Machining (grinding, drilling, sawing, polishing)	Final shape or dimensional tolerance
	Additives/final assembling	Quality control
Sorting, packaging and storage	Process according to the product	Quality control, Stock control

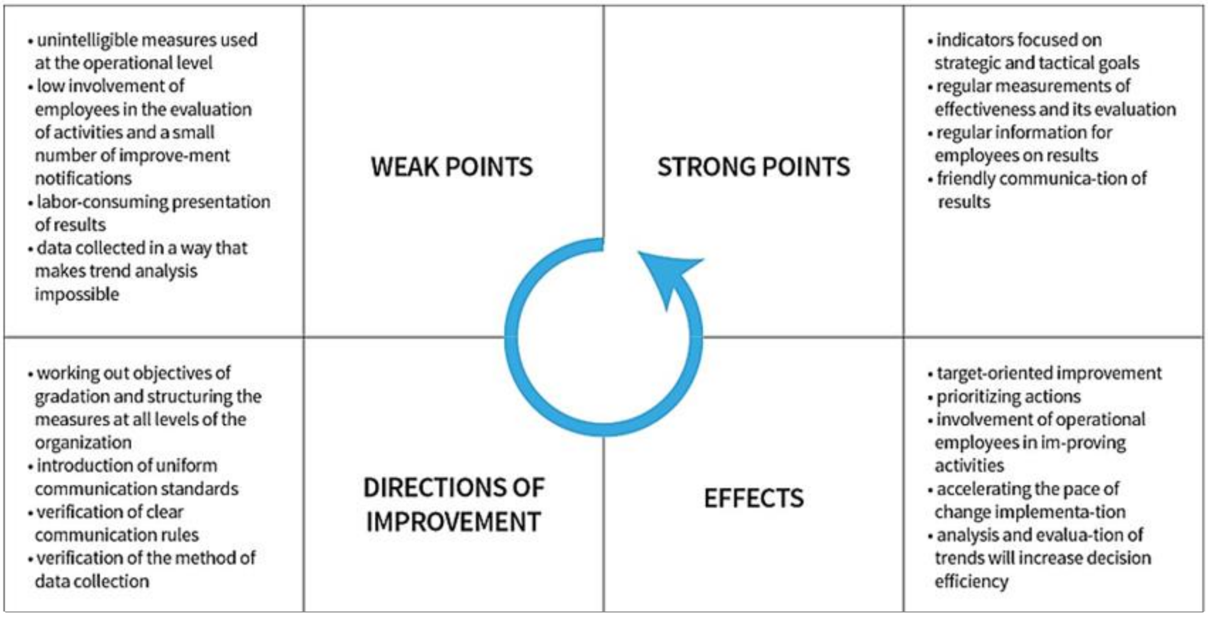

Figure 12 - Identification of barriers in refining processes in the ceramic industry [52]

Machine learning algorithms are already being used in ceramic industry, especially in quality control processes. With various algorithms, it is possible to predict the behaviour of the material under extreme temperature conditions and to detect anomalies and deficiencies in the tiles. The studies being carried out with the help of Artificial Intelligence (AI) seek to predict the anomalous behaviour of materials during the manufacturing process, making it possible to control and use the components that meet better resistance conditions than those currently being manufactured. By recognizing incorrect patterns, they are able to detect anomalies in products early, reducing shrinkage and increasing profitability. Nexusintegra already found companies that are working with this technology and are using it in this line or in others. They are, above all, companies in the ceramic, porcelain stoneware and flooring sectors [53].

Recent developments in AI&BD include real time monitoring, process optimization and programming, design improvement, quality control.

- Color Management software which allows ink savings and a quality improved designs thanks to mathematical algorithms (Digit-S)
- Data collection generated by advanced sensors, real time monitoring and remote monitoring of smart moulds for ceramics, optimization of warehouse management and freight transfer flows (DataRiver)
- Automated optical inspection designed to automatically find flaws in ceramic tiles before mass production (defect detection of the tiles to determine acceptance and rejection conditions (RSIP Vision)
- Real-time monitoring of production and sales performance

There is a growing interest in Big Data implementation among ceramic companies in their management and decision-making processes. Research results show that the use of new information technology in ceramic companies is already in its infancy and is gradually growing. Today, special focus is on the process of production, sales, product development and maintaining and improving business turnover. [54]

The following table shows an identification of sensor to get the insights through Big Data Analytics:

Table 4 - Identification of sensor to get the insights through Big Data Analytics in ceramic industry [55].

PROCESS	SENSOR	DESCRIPTION
Firing/flourishing	Thermocouple sensor	Used to monitor the temperature
Firing/flourishing	Proximity sensor	Used to measure and control the rotational speed
Sorting/Packages Stage	Planner sensot	Used to check the surface planarity
Sorting/Packages Stage	Linear sensor	Linear sensor used to check the linearity of the ceramic biscuits

5.8 CEMENT SECTOR

In [62], the key steps of the cement manufacturing process were defined as: (i) mining, (ii) crushing, stacking, and reclaiming of raw materials, (iii) raw meal drying, grinding, and homogenization, (iv) Clinkerization, (v) cement grinding and storage and (vi) packing. Furthermore, [57] states that cement manufacturing is a complex process starting with mining and then grinding raw materials such as limestone and clay to a fine powder, which is then heated to a temperature up to 1450 °C in a cement kiln. In [58], on the other hand, the manufacture of (Portland) cement is defined as having four main stages: (i) crushing and grinding the raw materials, (ii) blending the materials in the correct proportions, (iii) burning the prepared mix in a kiln, and (iv) grinding the burned product, known as "clinker," together with gypsum (which controls the setting time of the cement).

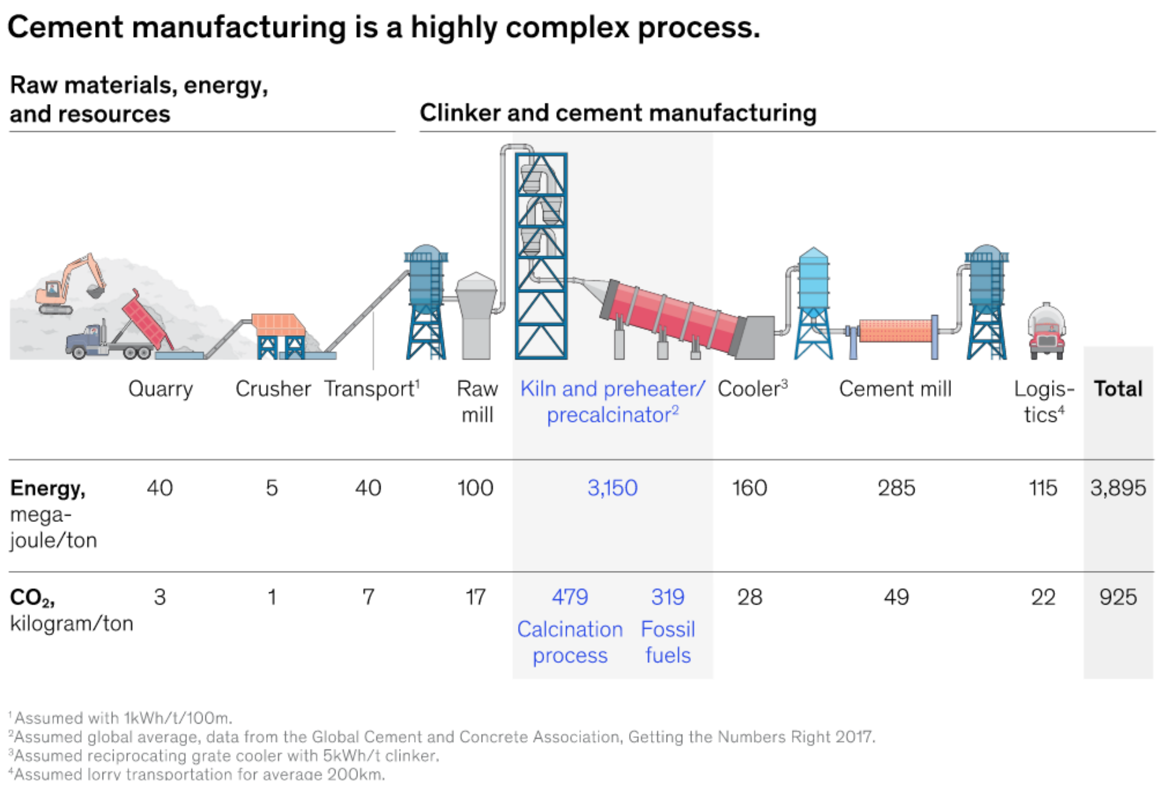

Figure 13 - McKinsey report summary of cement manufacturing processes. Source: https://www.mckinsey.com/industries/chemicals/our-insights/laying-the-foundation-for-zero-carbon-cement

A study by Ernst and Young [59] focuses on the aspect of sustainability and ecological aspects. It is said that cement is an essential component for the construction industry, but it also is a key prejudicial element for climate change, being responsible for 6 to 9% of global CO2 emissions. Due to new international agreements to minimize climate change, the cement industry is facing increasing pressure, and are already starting to address relevant issues. Example measures are, for example: to improve thermal energy efficiency and fuel switching, reduce the clinker-to-cement ratio, and the use of innovative technologies.

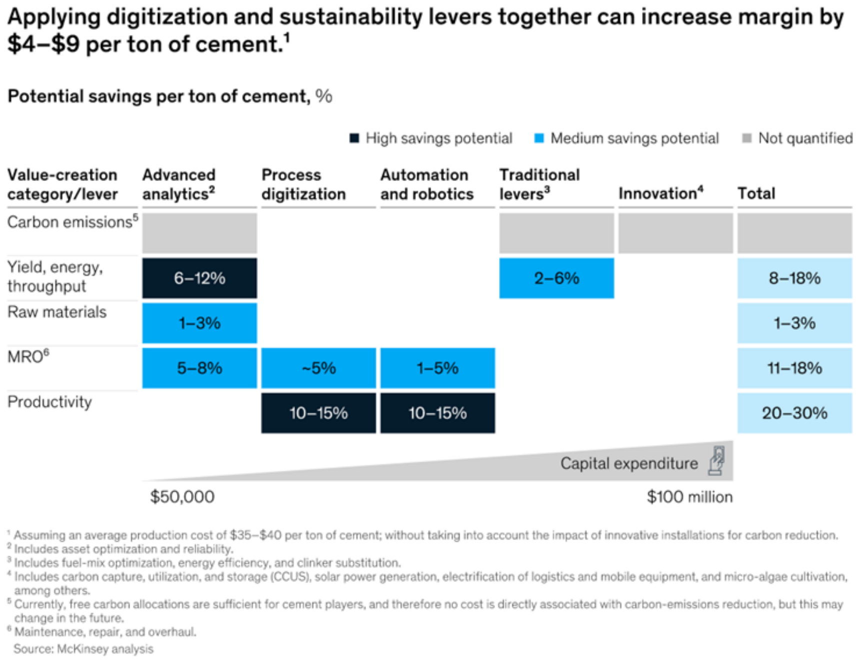

Figure 14 - McKinsey report summary of margin gains due to digitalization and sustainability.

A McKinsey report [60] gives a vision for the cement plant of the future, leveraging digitization and taking on board sustainability measures. The report goes on to indicate desirable objectives such as lower operating costs and higher asset value through higher energy efficiency, yield, and throughput. Also, the use of better targeted and effective maintenance to lengthen the lifetime of equipment. The environmental footprint should be minimized, thus facilitating its license to operate across locations and jurisdictions. In order to meet customer demand, a plant needs to dynamically adjust production and logistics according to real-time customer data, which opens possibilities for data mining and big data processing to synthesize and provide decision support information to managers who may be at remote locations. The report indicates that the cement industry is somewhat behind the curve in the adoption of digitalization, and ranks low in the ranking of Industry 4.0 leaders. However, the cement industry is now faced with greater regulations and less demand hence there is a need to leverage digitalization in order to keep a competitive edge.

The paper by Rodrigues and Joekes [61], also focuses on the environmental challenges faced by the cement industry. It is cited that concrete production (in 2009) was over 10 billion tons, including concrete and mortar. Cement is a key component for building and infrastructure and therefore has a special economic and social relevance. However, the industry is also one of the biggest polluters. According to the authors, cement production releases approx. 6% of all carbon dioxide generated by human activity, and accounts for about 4% of global warming. Possible areas of leverage of technology to mitigate this problem can be found, for example, in cement chemistry (sustainability), alternative materials and material recycling.

The next two references focus more specifically how AI and BD can be used in the cement industry. Firstly, [62] focuses on the high energy use in cement production, citing the consumption of 349 trillion thermal units of energy in the year 2019. Hence, cement plants are looking for innovative ways to reduce energy consumption and costs.

The argument is made for artificial intelligence for cement plants, citing the following possible application areas:

- Failure prediction (operative and corrective failures);
- Production processes optimization;
- Predictive maintenance;
- Remote operation; and
- Product design and quality; smart supply chain.

An example is given of how a global cement company has taken on board AI solutions. Cemex, a major building material company contracted a specialist AI company (Petuum) to implement the industrial AI products. The first product (Industrial AI Autopilot) claims to use Machine Learning and Deep Learning support complex process control to obtain a better optimization (superior to a human operator). The authors state the system uses deep learning neural networks trained with two years of plant information, including data from cement processes with associated timestamps.

The next AI product focuses on "Modeling for decision making", which models the variable inter-relationships over time. The historical operating models provide support for the current evaluation and future prediction of process performance.

Following on from the previous product, AI-based models are used to provide optimal settings, which are recommended for the plant. Plant data is analysed to optimize and predict process behaviour. For example, the AI system will recommend optimum settings for control variables in real-time, which are then validated by human operators before applying them.

The software "back-end" of the AI Autopilot product integrates historical process data via a data infrastructure, processing historical and streaming data, used to make the predictions.

Finally, [63] gives some more examples of how the Peetum software described in [68] is applied to specific steps and processes in the cement production process. It is said that the AI model used for cement uses smart factory principles to optimises the whole manufacturing process. This includes AI optimization for the cooler, ball mill, vertical mill, and the complete pyro process which includes pre-heater, cooler, and kiln. The AI model learns the dynamics of each of the industrial assets (cooler, ball mill, vertical mill, pre-heater, and kiln) and processes from historical sensor data, creating prescriptions by searching for the optimal values of critical control parameters, and closing the loop by sending prescriptions back to assets and processes to be activated.

6. CONCLUSIONS

One of the objectives of this document has been first to obtain a vision of the current landscape of the key SPIRE industry processes on a sector-by-sector basis, **highlighting issues and bottlenecks, and identifying potential key application areas for AI and BD technologies**. This has been detailed in Section 5.

As a complement to this first industrial analysis, a list of key industrial stakeholders will be identified through a focused analysis of the stakeholders showing direct connection to the consortium companies and other relevant actors in the EU scenario.

As a second objective, we have captured feedback and information from stakeholders, and of real current projects from the 1st AI-CUBE online Industrial Workshop, which has been summarized in Section 8.1 and detailed in Annex 8.1.

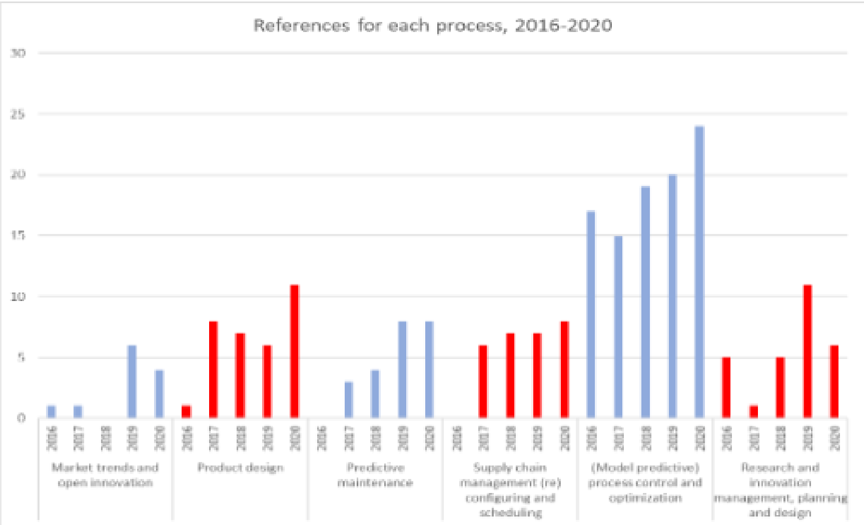

Figure 15 – AI and BD literature references(EU + International) found per process: 2016-2020 (D1.1)

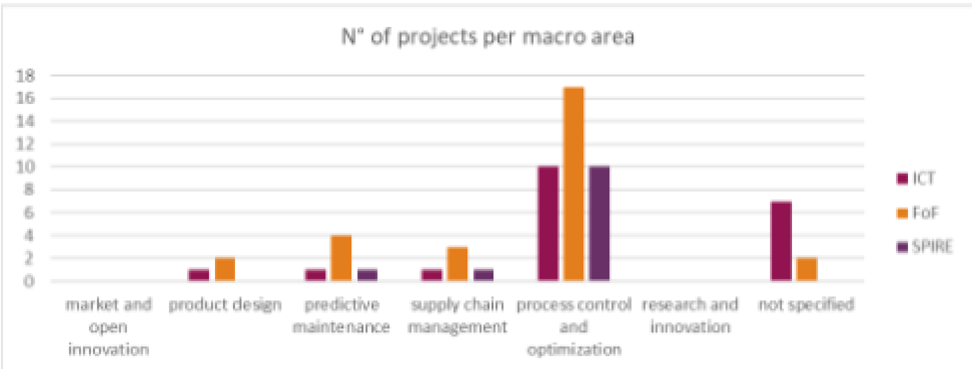

Figure 16 – Number of European projects involving AI vs process macro-area (from

This Deliverable adds to the previous results of the literature and project analysis carried out, where some first indications of (possible) AI and BD focus, in the different process industries may lie. In D1.1. this was visualized through the graphs in Fig. 15 (EU + International)

A similar picture emerged from an analysis of funded European projects, confirming a focus on process control and optimization, product design, predictive maintenance and supply chain management (Fig. 16). The information for Fig. 16 was obtained by searching European public domain databases.

Clearly, each SPIRE sector has its own challenges, where AI and BD can add value, and as a result differences in AI &BD focus as well as maturity start emerging, as sustained in the current Deliverable.

6.1 MAPPING TO THE "CUBE": TECHNOLOGIES VS PROCESSES AND SECTORS

To summarize the sector-by-sector review of the key processes given in Section 5, it has emerged that some sectors are leaders in digitalization, such as the water sector, chemicals and engineering, whereas other tend to lag behind, such as the ceramics and cement sectors. However, many sectors have similar problems, such as **high energy usage and complex process behavior**, as in the steel, minerals, non-ferrous metals, water, ceramics and cement industries. This issue is a good candidate for optimization and improved process control through AI and BD.

Another key issue in many highly industrial environments is **predictive maintenance** in order to avoid failure of major physical components due to "wear and tear" of the production processes. Also, quality control and the prevention of situations which arise in defects which is particularly important in the **ceramics industry**.

Within the **chemical industry**, the bio-based sub-sector often involves new experimental processes which need to be optimized and controlled efficiently, as well as scale-up of processes and consumer centric production. 3D printing and intelligent stock control have also been suggested as potentially adding value to the bio-based industries.

The **engineering sector** on the other hand is transversal and is applied to many other sectors such as chemicals, where it often leads in introducing digitalization to these sectors. For example, digital twin simulations, monitoring of critical infrastructures, workplace security and healthcare.

On the other hand, the **non-ferrous metals**, **steel and cement** industries suffers from high throughput volumes and extreme processing conditions (such as temperature) and a complex chain of processing steps. The minerals industry has similar issues, including safety in the mining extraction process and **high energy consumption**.

The **water sector** displays quite a variety of applications of new technology projects, and the key issues involve the main processes found in this sector which are the efficient treatment of waste water on the one hand, and the secure production of clean water for human use and consumption on the other. Both of these aspects present challenges due to varying real world conditions and the large scale of the infrastructures and installations involved.

Regarding the adoption according to the company size, in general large companies tend to invest in AI faster at scale [37]. This is typical of digital adoption, in which, for instance, small and midsized businesses have typically lagged behind in their decision to invest in new technologies. However, it should also be taken into consideration that large companies may subcontract digitalization and specialized technology work to smaller third-party companies/consultants which are specialized in, for example, the deployment of AI/BD technologies in specific industries.

Table 5 shows a summary of the identified cases from Section 5, the workshop and the stakeholder feedback to date. **It shows that in terms of processes,** "(Model predictive) process control and optimization" is the most frequent in all sectors, whereas "Market trends and open innovation" does not appear at all. Hence the latter process represents an opportunity for all process sectors to apply AI and BD. For example, the cement sector depends on the demand from the construction industry which in term depends on public and private spending in housing, infrastructures, etc., as well as new trends in building materials, safety requirements and legislation. The interaction of these factors and trends have a complexity where AI algorithms can be used to help with forward planning.

We recall from Deliverable 1.1, the exercise to build a taxonomy and common terminology of technologies for artificial intelligence and big data. To recap, AI was classified into three macro areas, **"perception and communication"** (Data understanding and characterization, Natural language processing, Object and spatial recognition, Machine learning); **"cognition and reasoning"** (Intelligent planning, Expert systems, Case based reasoning) and **"transversal/integration/interaction"** (Intelligent agents, Cyber-physical systems).

Likewise, Big Data was classified into five macro-areas: **data processing, Computing and storage infrastructure, Data protection, Data visualization and Data management**.

With reference to **Table 5, in terms of technologies**, it can be seen that "Machine learning" and "data understanding and characterization" are the most frequent for all sectors and processes. These are followed by "Intelligent planning" and "Cyber-physical systems". Least used technologies are "intelligent agents and natural language processing".

With reference to Table 5, we can also mention the aspect of whether there are technologies that are sector-specific (or more present in certain sectors) and which ones are general to all sectors. It can be seen that "Machine learning" appears in all sectors, whereas "data understanding and characterization" appears in six sectors (water, minerals, engineering, chemicals, ceramics and cement), but not in (steel, non-ferrous). It would seem logical that "data understanding and characterization" would also be relevant to the last two sectors, but the work is not necessarily published in the public domain and/or is due to the limitations of the information retrieval (search repositories and keywords). "Cyber-physical systems" also appears in all sectors but one (ceramics). At the other extreme, "object and spatial recognition" is the technology which appears in the least sectors (only engineering), as well as "case based reasoning" (only non ferrous). This may be again an issue relating to information retrieval limitations (keywords). In general, it could be said that all the given technologies are applicable to any of the eight process sectors, but are more present (or identifiable) in a subset of sectors.

In terms of needs and challenges on a sector by sector basis, this is more difficult to evaluate from "state of the art" literature surveys, and indeed will be a recurrent theme throughout the project where surveys and live stakeholder meetings will provide valuable input. It can be said that two general challenges (though not the only ones, the specific challenges are detailed in Table 5) facing process industries in the coming decades will be (i) energy consumption and (ii) transition to a green economy, which are also inter-related. Artificial intelligence, through data driven modeling, simulation, digital twins and smart sensors, among other technologies, can play a key part in optimizing energy consumption and indeed making possible new paradigms for industrial processes. Energy consumption is especially critical in sectors such as steel, cement, chemicals, ceramics. On the second point, transition to a green economy for most sectors probably implies changes in materials used and processes, which requires re-calibration and definition of many systems, and careful evaluation of cost/benefit. Sectors particularly affected by green transition would be chemicals, minerals, cement, ceramics, where alternative materials could imply major changes in processing technology. Artificial intelligence and big data can play a key part in supporting this change, by sensor data capture and exploitation (e.g. smart sensors), which will be a challenge in more "traditional" environments, such as cement and ceramics. However, it would be wrong to generalize only on a sector, and ability/willingness to introduce and utilize new technologies can, with a sector such as ceramics, vary on a factory to factory basis, as well as in different countries within the European Union (e.g. stronger players such as Germany/France vs developing countries which have more recently incorporated in the EU, such as Poland, Hungary, Lithuania, Slovakia. Indeed it is relevant to mention here that the now 27 EU countries do not represent a homogenous mix, in terms of degree of industrial development, with 8 countries (mainly central and eastern European) joining the EU just since 2006.

Hence, these finding will be used as an input to Deliverable 1.3 to further develop and establish the "cube" dimensions.

Table 5 – Summary by (cube) sectors and processes, issues and potential AI/BD applications

Sector	Process	Needs/Challenges	Corresponding AI/BD technologies
Water	(Model predictive) process control and optimization Predictive maintenance Research and innovation management, planning and design	Needs: waste water processing, clean water processing. Challenges: complex processing chain, large processing volumes, yield.	Machine learning, Data understanding and characterization, Expert systems, Cyber-physical systems.
Steel	(Model predictive) process control and optimization Supply Chain Management	Needs: efficient furnace operation and smelting. Challenges: High energy consumption, risk to humans, quality control, logistics, Value Chain.	Machine learning, Cyber-physical systems, Intelligent planning.
Minerals	(Model predictive) process control and optimization Predictive maintenance	Needs: efficient milling of raw material, mining/extraction, scheduling/planning, security, automation, remote monitoring. Challenges: high energy consumption, security and human safety,	Machine learning, Data understanding and characterization, Intelligent planning, Cyber-physical systems (SLAM Self Driving Vehicles)
Non-ferrous metals	(Model predictive) process control and optimization Predictive maintenance	Needs: furnace, smelting, scrap quality control, logistics. Challenges: high energy consumption, risk to humans,	Machine learning, case based reasoning, Cyber-physical systems

Engineering	(Model predictive) process control and optimization Predictive maintenance Supply Chain Management	Needs: quality assurance, predictive maintenance, sensor data capture. Challenges: fault detection, data quality.	Machine learning, Data understanding and characterization, Cyber-physical systems, Object and spatial recognition, Intelligent planning.
Chemicals	Supply chain management (re)configuring and scheduling (Model predictive) process control and optimization Research and innovation management, planning and design Supply Chain Management	Needs: optimum conversion of materials. reliability, production planning, continuous sensor-based monitoring process control logistics, goods shipments tracking. Challenges: waste avoidance, process complexity.	Machine learning, Data understanding and characterization, Intelligent planning, Expert systems, Cyber-physical systems.
Ceramics	Product customization/design Supply chain management (re)configuring and scheduling Model predictive) process control and optimization Research and innovation management, planning and design	Needs: optimum raw material processing, firing, finishing. Challenges: high energy consumption, reduction of defects (cracking/foaming)	Machine learning, Data understanding and characterization, Intelligent planning.
Cement	Predictive maintenance (Model predictive) process control and optimization Product design Research and innovation management, planning and design Supply chain management	Needs: optimization of kiln, firing, material processing, predictive maintenance, predict process behavior, supply chain, remote operation. Challenges: high energy consumption,	Machine learning, Data understanding and characterization, Intelligent planning, Cyber-physical systems.

6.2 SUMMARY 1ST AI-CUBE INDUSTRIAL STAKEHOLDER WORKSHOP

The webinar, virtually hosted by IRIS, took place on February 2nd, 2021, and brought together representatives from SPIRE2030, Mabxience, Aqualia, Fraunhofer IPT and Universitat Politecnica de Catalunya which shared their experiences, vision, objectives, and challenges faced in the journey towards the process industry of the future, while presenting case studies related to the involvement of the AI and BD technologies in the SPIRE 2030 industries. Refer to Annex 9.1 for more details.

To summarize the use-cases presented in the workshop (detailed in Annex 8.1), the five presentations covered the chemicals, engineering, water and minerals sectors. The **chemicals/engineering** use case presentations highlight the challenges for data capture from in-line sensors and subsequent data preparation, formatting and processing in order to guarantee a quality input to the data modeling stage. Also, the need for good metrics in order to measure the results and compare with baselines in order to evaluate the improvement with respect to current methods. Also, the data scientist expert know-how is key for choosing the most adequate algorithms for a given problem and type of data. Deployment is a key issue for which a clear idea is necessary from the beginning, in order to make real use of the results in the production environment. Another key aspect is using appropriate techniques and pre-processing for treating time series data and sequences of processes where time is a critical factor.

The **water sector** use case presentations highlighted again the key aspect of having the right sensors in place to capture the right data, have clear objectives for the data modeling and decision support in collaboration with the plant engineers. Also, the importance of combining the data driven modeling with "a priori" background information about the industrial domain, in the form of human expert defined rules as well as key documentation regarding procedures and key relevant knowledge.

Finally, in the **minerals/mining sector**, the identification of energy consumption was a key aspect to study, where a small reduction can have a large positive effect due to the high volumes involved. The difficulty of conducting experiments with a wide range for control parameters was identified which is often limited by physical restrictions of the process itself, such as rotation speed of the grinding mill and the throughput rate of the material.

Several of the issues mentioned in the case studies were similar, such as using the right sensors based on use-case and data-analytics strategy, capturing the right data, need of combining data driven approaches with relevant “a priori” background information, data quality, among others.

The workshop material contributes to the overall preliminary conclusion/input for further to-be-analysed challenges for AI & BD deployment in the process industries at large, i.e. to be taken into consideration in the next analysis work of AI-CUBE.

6.3 OVERALL SUMMARY AND STAKEHOLDER IDENTIFICATION

Table 6 contains an initial stakeholder/key player list obtained from different sources: (i) Information search by sector for Section 5 (11 organizations), (ii) Workshop invited speakers (4 contacts, coloured light brown), (iii) feedback from survey questionnaire (to present date, 6 contacts, coloured light grey).

Also, a database search by PNO, resulted in a list of 200 potential stakeholders. From this list, the following are a sample: ABB Group, ArcelorMittal, Dow Chemical Company (DowDuPont), German

Research Center for Artificial Intelligence – DFKI, Hydro Aluminium Deutschland GmbH, IBM, Mondragon Sistemas Group, Rio Tinto Group, Royal Dutch Shell, SAP AG, SIEMENS AG, Swedish Hydro Solutions AB, Swiss Steel, University of Cambridge, University of Skövde, University of Twente and WORLDSENSING SL.

More extensive details are also given in Deliverable 2.1 of the stakeholder engagement plan, which is a confidential document.

Table 6 – Initial stakeholder list

Name	Sector	Comments
Mabxience	Engineering / Chemicals	Invited speaker at workshop. Predictive maintenance. Engineering company, installations maintenance.
Aqualia/FCC	Water	Invited speaker at workshop. Optimum process control
Fraunhofer IPT	Engineering	Invited speaker at workshop. Customized process control.
Universitat Politecnica de Catalunya (UPC)	Water	Invited speaker at workshop. Optimum process control.
Lubelska University of Technology	Power	Replied positively to post workshop survey and indicated would like to become a stakeholder
Lortek	Engineering	Replied positively to post workshop survey and indicated would like to become a stakeholder
Kando.eco	Water	Replied positively to post workshop survey and indicated would like to become a stakeholder
Idener.es	Engineering / Chemicals	Replied positively to post workshop survey and indicated would like to become a stakeholder
Berlin Centre of Competence for Water (kompetenz-wasser.de)	Water	Replied to post workshop survey and indicated they might like to become a stakeholder
De Watergroep is the largest drinking water company in Flanders (dewatergroep.be)	Water	Replied to post workshop survey and indicated they might like to become a stakeholder
Merck	Chemicals	Has done important studies on AI/BD applications such as "intelligent supply chains"
BASF	Chemicals	The "supercomputer" Qriosity used for research and predictive maintenance in the area of maintenance and repair from Evonik Industries.
University of Münster	Chemicals	Organic chemist Segler at the University of Münster has succeeded in achieving results that are 30 times faster with the help of artificial intelligence in retrosynthesis
CEMEX /Petuum	Cement	A specialist AI company (Petuum) contracted by CEMEX.
International Water Association	Water	Kalanithy Vairavamoorthy, Executive Director

European Steel Technology Platform	Steel	Ref. [19]
MOgroup process services. https://www.mogroup.com	Minerals	Major European service company dedicated to the mining industry Ref. [23]
LKAB	Minerals	Major mining company
Outotec	Minerals	Mining industry consultants
RSIP Vision	Ceramics	Technology company with automated optical inspection system designed to automatically find flaws in ceramic tiles before mass production (defect detection of the tiles to determine acceptance and rejection conditions
DataRiver	Ceramics	Technology company with system for data collection generated by advanced sensors, real time monitoring and remote monitoring of smart moulds for ceramics, optimization of warehouse management and freight transfer flows

Following the work carried out in this deliverable D1.2, including pro-active further engagement with identified additional stakeholders, the next steps envisaged are as follows: **(a)** development work on Task 1.3 will consolidate the knowledge obtained from Tasks 1.1 and 1.2 and **(b)** set the stage for the WP2 tasks; **(c)** contacts with stakeholders will be consolidated in order to develop a cohesive working group and network.

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8. ANNEXES

8.1 ANNEX – 1ST AI-CUBE ONLINE INDUSTRIAL WORKSHOP - PRESENTATIONS

The following summarizes the material obtained from the **1st AI-CUBE online Industrial Workshop** organized by the AI-CUBE project, and held on 2nd February 2021, with key invited speakers from different industries and real projects. Five real use cases were presented, two from the water sector, two from chemicals/engineering, and one from the minerals/mining sector, which are summarized in the following sections.

The webinar, virtually hosted by IRIS, brought together representatives from SPIRE2030, Mabxience, Aqualia, Fraunhofer IPT and Universitat Politecnica de Catalunya which shared their experiences, vision, objectives, and challenges faced in the journey towards the process industry of the future, while presenting case studies related to the involvement of the AI and BD technologies in the SPIRE 2030 industries.

The webinar commenced at 14h with an overview of the AI-CUBE project by PNO coordinator Chiara Eleonora De Marco, with special emphasis on the three "dimensions" (thus the cube) of the project analysis: sectors, processes and technologies, the 8 SPIRE process industry sectors considered, and the stakeholder involvement. This was followed by a presentation by Mrs. Angels Orduña, Executive Director of SPIRE 2030, on the r*elevance of AI and Digital tools for the process industries in order to achieve the Processes4Planet Roadmap 2050.*

Next, five case studies were presented for different process sectors. Mr. Javier Rodriguez, Engineering and Maintenance Manager Mabxience (Spain) presented a case study of artificial intelligence with big data applied to condition based maintenance in a Water for Injection (WFI) plant. Next, Mrs. Ledicia Pereira, Project Manager at the Innovation and Technology Department FCC Aqualia (Spain). presented the case study "Optimising Water Industry Processes Using Machine Learning: Case Study at Lleida Wastewater Treatment Plant for optimising sludge management line". This was followed by the presentation of Mr. Maik Frye, Research Associate of Fraunhofer IPT (Germany) entitled "Machine learning based product quality prediction in profile extrusion processes". Next, Prof. Karina Gibert of the Universitat Politecnica de Catalunya (Spain) presented a case study of "*AI applied to a waste water treatment plant", and finally Dr. David Nettleton of IRIS presented a case study of "Predictive modeling for heating control in a mining facility" on behalf of LKAB and Outotec who participated in the study.*

The presentations were followed by a question/answer session and discussion where the attendees could place their questions in the Teams app chat and the presenters could give their replies. Issues were raised such as the need for quality data (esp. from sensor data capture), the incorporation of expert human knowledge to support data driven models, and deployment. The workshop concluded at 1630h will thanks to all the participants and attendees. From initial feedback, several organizations have confirmed their interest in participating and becoming stakeholders of the project and an online survey questionnaire was made available to all attendees to obtain further feedback.

8.1.1 Case study of Artificial Intelligence with Big Data applied to Condition Based Maintenance in a Water For Injection (WFI) Plant

In the case of the chemicals/engineering sector, the first presentation by Mabxience was a case study of AI with BD applied to condition based maintenance of a water for injection (WFI) plan. The Engineering and Maintenance Manager first gave an overview of the WFI plant and the problem of predicting maintenance requirements to anticipate unexpected events/failures. The approach was to install a comprehensive sensor system in which temperature, pressure and conductivity were measured in strategic points of the water circuits. Data was captured over a four year period, together with alarm data and water quality. This data pool was then used to analyse trends and build predictive models on the 2018 data, and then test on the 2020 data. It was found that the chosen 2020 events were predictable using models trained on the 2018 data. A rule induction algorithm was used which has the advantage of "explaining" in terms of rules, the model functionality. Previously, neural networks (black box) had been used more generically (to identify anomalies). An AUC (Area Under Curve) metric was used to quantify the sensitivity of the predictive models in a 14 day time window before the maintenance events. There models were found to have a good sensitivity with respect to detecting the events *a priori* in the 14 day time window. An event would be, for example, a malfunctioning sensor or valve, or tube rupture. The results form the basis for a future "expert system" support system for the operations manager to anticipate unplanned maintenance events.

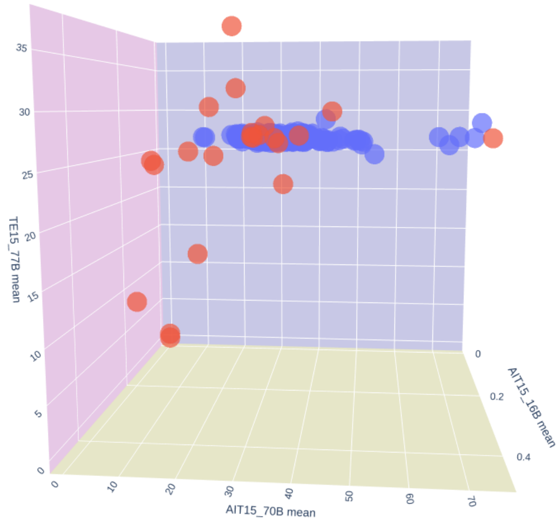

Figure 17 - Chemical/Engineering sector: 3D representation of anomalies (red) and normal cases (blue) based on temperature and water conductivity sensor data

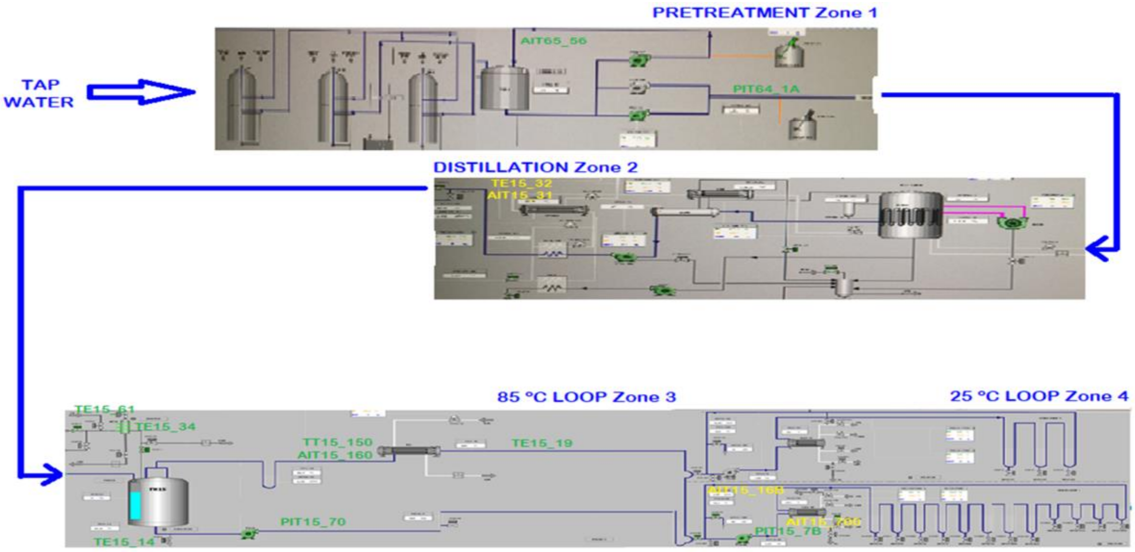

Figure 18 - Chemical/Engineering sector: schema of the WFI plant

8.1.2 Machine Learning Applied to Optimize Water Treament Plant Processes

The first water sector presentation by FCC/Aqualia dealt with optimizing industry processes using machine learning, at the Lleida wastewater treatment plant for optimising the wastewater treatment line. Two case studies were presented: (i) Enhancement of biological nutrient removal process with intelligent assisted control tools in full-scale wastewater treatment plant and (ii) Development of self-controlled polyectrolyte system for sludge dewatering.

Figure 19 - Lleida waste water treatment plant

In the first case, sensors captured information about chemical constituents, as well as flow-meters, energy meters and state of control elements. The previous input characteristics to the system were WWTP, non-AC system, manual control; and the output characteristics included a low nutrient removal yield, lack of compliance with outflow requirements, high staff dependence and unwanted chemicals in dewatered sludge. With the new AI assisted system, the new inputs were an upgraded WWTP, and AC systems; the new outputs were a high nutrient removal yield, compliance with outflow requirements, automated control system, lower unwanted chemical presence in dewatered sludge and reduced chemical and energy consumption.

In the second case, a circular control circuit was defined: sludge → centrate → control→ polyeletrolyte dose → sludge ... which effectively passed from a manual method to an automated one, achieving a decrease in polyelectrolyte consumption.

Overall, a key aspect is implementing a smart metering and control loops for process optimisation, which will go towards a machine learning capability to produce predictive models. The inputs to the machine learning modelling are a dataset, an optimization metric and a set of constraints (time/cost).

8.1.3 Machine Learning Based Product Quality Prediction in Profile Extrusion Processes

The presentation corresponding to the engineering sector, presented by the Fraunhofer Institute for Production Technology (IPT), described a case study of machine learning based product quality prediction in profile extrusion processes. Different focuses were proposed for applying ML to production: process (design, management, optimizing of routing & scheduling, predictive process control); machines & assets (anomaly detection, predictive maintenance (PdM), self-learning machines); product (product-design).

A key success factor presented was the "ML pipeline", which has as main steps (data integration, data preparation, modelling and deployment). The data integration phase includes use case selection and IT system analysis. The data preparation phase is crucial, as data quality depends on this, which includes pre-processing, "feature engineering" and data and process understanding. The modelling part includes algorithm selection, tuning of the algorithm control parameters, training and evaluation. The deployment part covers deployment design, testing, monitoring, retraining and certification. The use case covers a sequence of processes, ending in quality assurance.

The objective is to predict the expected product quality at an early stage on the process-chain, aiming to minimize scrap, machine downtime and repair costs. The learning task deals with a classification problem, to distinguish products that are expected to be OK and products which are expected to fail.

The data preparation commenced with a dataset of 194 attributes. After removing null attributes, non-changing values, attributes with a high number of missing values, and highly correlated attributes, this left a subset of 33 attributes. This was further separated into non-categorical data and categorical data.

For the application of ML-models, two algorithms were tried: decision tree and random forest, which gave similar results, the former 91 % accuracy and the latter 95 % accuracy.

In order to evaluate the results, different criteria were used: the performance was compared to the business objective, its return on investment, transparency, training time, model scalability, if the model was transferable to similar use-cases and if the process is still compliant to obtain certification.

For deployment, a GUI allows a simulation to be run: first select the product, then the decision trees are trained to predict the quality of the product. When the simulation terminates it shows a screen with the product information, the prediction analysis and the features used. Also, the decision tree is shown on the screen so the user can see how the model has reached a given conclusion.

In summary, a roadmap has been developed to achieve deployment of AI/ML in production, beginning with strategy, followed by choice of projects, use case creation, data preparation and quality assurance and culminating in ML based generation of knowledge.

8.1.4 AI Applied to a Waste Water Treatment Plant

The second water sector presentation was presented by the UPC and dealt with AI applied to a waste water treatment plant. Data was obtained for 41 biochemical parameters (25 relevant), flows, solids, organic matter, pollutants, biomass of 396 daily means between 01/09 and 30/09. Prior expert knowledge was aggregated to this data. The case to study is decision making under abnormal plant operation. The objective is to re-establish normality as soon as possible to the plant.

The waste water treatment plant has the following characteristics of treatment (pre-treatment, primary and secondary treatment) and measurement points (entry, settler, bioreactor, exit).

In the application, it was important to include prior expert knowledge acquisition (legal limits of pollutants) as a knowledge base of rules. The methodology was to perform clustering based on rules, then use the knowledge base to find the rule induced partitions, different classes and the residual. Next, hierarchical clustering was applied to the new dataset to determine the final classification, which is consistent with the prior knowledge. The classification (hierarchical tree) facilitates interpretability.

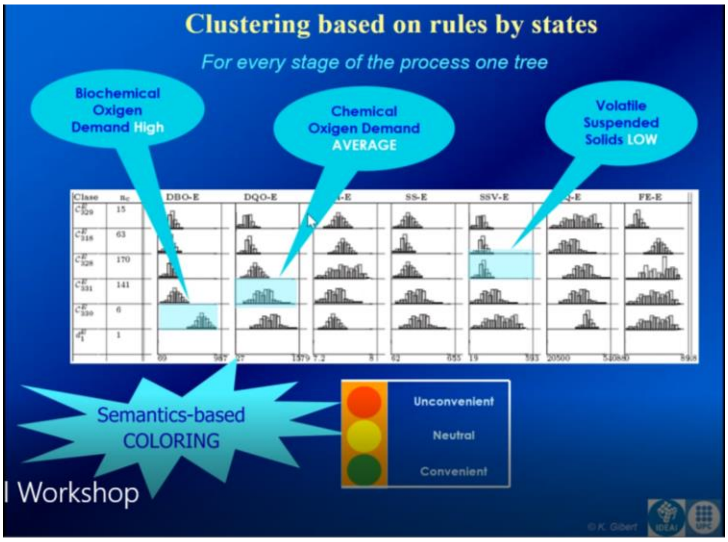

Figure 20 - Water sector decision support screen interface

The class interpretation uses multiple boxplots versus classes to identify outliers in order to characterize variables which have exclusive values for a given class. Then, for a fourth class, almost all the variables take few values. As an example, the expert opinion would then interpret for this class, that the input valves are closed, with minimum purged flow and system protecting is active, which corresponds to "storming days".

For every stage of the process a tree is defined and for each tree decision support assigns a panel graph, a thermometer and traffic light panel (see Fig. 17). This provides a semantics based colouring, for example: biochemical oxygen=high (red), chemical oxygen demand=medium (ambar) and volatile suspended solids=low (green).

For deployment of the decision support system, the following three steps were implemented: (i) measures of one day → (ii) use generated rules for finding corresponding class → (iii) apply the treatment/action associated to that class

In conclusion, two key aspects were the support of prior domain knowledge/processes, and the incorporation of semantics using a thermometer for automatic interpretation with colour indicators.

8.1.5 AI Applied to Energy Optimization of a Milling Machine for Iron Ore Grinding

In the case of the minerals/mining sector, IRIS gave the presentation on behalf of the operations manager of LKAB and Outotec mining consultants. The case study deals with AI applied to energy optimization of a milling machine for iron ore grinding at the Kiruna mine in Sweden. First, the mining installation at Kiruna was described, which is the largest underground iron ore mine in the world. Large grinding cylinders (10m by 7m) are used to break up the raw material (rocks) which arrive from the mine into smaller pieces. The grinding cylinders require a large energy input in order to function however they are very inefficient as 90% of the energy is lost as heat, mainly from the exterior of the cylinder and adjoining components. Therefore, a study was conducted to measure the heat loss over a 3 day period, using two infra-red cameras pointing at the cylinders. This data was combined with the PLC machine control data, and several experiments were conducted, such as increasing/decreasing rotation speed and increasing water supply. The experiments were limited in scope/range as the grinders are in production and large changes could produce damage or stoppage. Rule induction models were built to predict the power supply as output given the temperature and control parameter values, and were compared with statistical models (regression) for the same data. It was possible to build a data driven system model with a high precision (95%) for the milling machine. The rule based model also gave insights about relations between the thermal images, the machine control parameters and the variations from the experiments. However, it was commented that the temperature of the surface of the grinder was rather homogenous due to the internal cladding of the cylinder, and a second useful future application of the thermal images would be to detect anomalies for preventive maintenance.

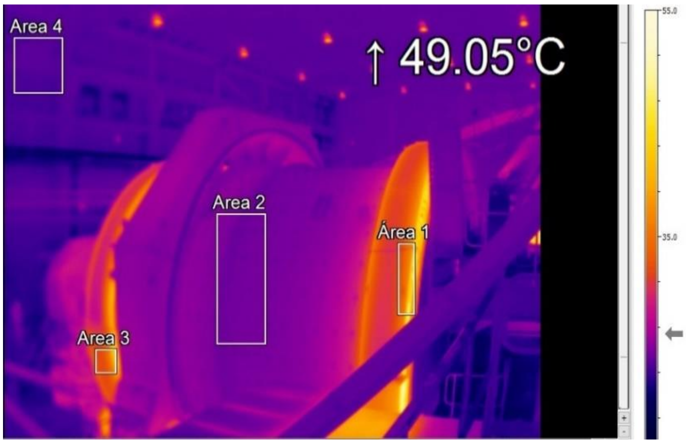

Figure 21 - Mining/materials sector: thermal image of mill cylinder with four interest areas defined.