European Lighthouse to Manifest Trustworthy and Green AI

Initial Report for Verticals

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Executive Summary

This document describes the first activities that occurred in the context of Work Package 3, where the four so-called "verticals" (Energy, Healthcare, Manufacturing, and Space) have undergone internal discussion for the gathering of use cases valuable of being exploited in the Open Call schemas in charge of Work Package 5. A detailed listing of these selected use cases, together with an accompanying text describing the overall context they were retrieved from, constitutes the central reporting part of this document and is deeply supported by scientific literature sources.

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1 Introduction

1.1 Purpose and Objectives

This deliverable, which is related to Work Package 3 (WP3), aims to highlight current and future scenarios, outline potential opportunities, and list the challenges that the targeted verticals face. Creating a well-organized plan for co-creation activities is essential to WP3. This involves a systematic approach that outlines precise objectives, deadlines, resource distribution, and performance indicators. Moreover, this approach promotes experimentation, prototyping, and validation through a series of workshops, open calls, and other collaborative initiatives, to gain innovation and drive tangible outcomes that address the identified challenges and exploit emerging opportunities.

1.2 Verticals

This deliverable is intended to give a general overview of the challenges inside the main verticals of the project: energy, healthcare, manufacturing, and space.

- **Energy vertical.** The energy sector presents both challenges and opportunities (use cases) for climate change adaptation, ranging from transitioning to renewable energy sources to improving energy efficiency and developing smart grid technologies. By analysing these challenges within the energy vertical, the aim is to identify opportunities for innovation and collaboration.
- **Healthcare vertical.** Recent technological developments in the healthcare industry produce enormous amounts of clinical Big Data, leading to challenging analytical problems. The lack of transparency in AI systems impedes their acceptance among practitioners. Moreover, the development of Responsible AI in healthcare is heavily influenced by ethical considerations like prejudice and trust. Ensuring model explainability and maintaining intricate datasets are critical technical problems.
- **Manufacturing vertical:** Cyber Physical Production Systems, which combine cyber and physical assets, are emphasized in Industry 4.0. Human-centric Manufacturing is now the main emphasis of AI-driven Digital Transformation, which integrates robotic technologies, machine vision, and decision support. With the integration of Green, Adaptive, Trustworthy, and Human-centric AI, the manufacturing field places a strong emphasis on production that is sustainable, circular, and resilient.
- **Space vertical:** The space sector is adopting AI across satellite operations, autonomy, , and Big Earth Data (i.e., hyperspectral/multispectral optical images, synthetic aperture radar (SAR) images, and atmospheric data) processing. AI developments can support space solutions and progress EU policy objectives (i.e., green deal, common agriculture, space, surveillance and tracking), particularly for satellite operations and earth observation (EO) applications.

Each of them proposes a series of challenges concerning the possible Artificial Intelligence (AI) technologies, setting them to a specific position of the pillars.

1.3 Structure of the deliverable

Based on the information provided, the structure of this deliverable is outlined as follows. Each subsequent section will detail a specific vertical, accompanied by a collection of use cases. Attached to each use case, the following information will be tabled:

- partners involved;
- description of the use cases goals, users and narrative;
- industry challenge and main drivers considering ENFIELD pillars;
- state-of-the-art;
- expected impacts and outcomes;
- AI requirements.

2 Energy vertical

This section aims to provide an overview of the context and challenges entailed in integrating AI within the energy sector. Additionally, it describes the use cases identified by industry and academia over the initial 6-month period of the ENFIELD initiative. These use cases exhibit considerable promise for leveraging the capabilities of AI across four fundamental research pillars: Green AI, Adaptive AI, Human-centric AI, and Trustworthy AI.

2.1 Context and motivation

Over the last 15 years, the energy sector has undertaken a structural transformation summarized by the 3Ds: decarbonization, decentralization, and digitalization (Di Silvestre et al., 2018).

The drive towards decarbonization has seen notable progress through intensified integration of renewable energy sources (RES). This involves strategic actions, such as replacing carbon-intensive technologies like coal power plants with large-scale RES power plants, increasing RES self-consumption rates among industrial, domestic, and transportation users, and electrifying vehicle fleets. Additionally, efforts extend to new energy vectors like green hydrogen and energy storage technologies, providing enhanced system flexibility, including seasonal storage, and at least keeping the security of energy supply. However, the substantial increase in RES introduces significant challenges in all energy system elements: generation, transmission, distribution, and consumers (Lopes et al., 2020).

Decentralization is being realized through various actions. This includes distributed generation technologies such as co-generation power plants, collective photovoltaic installations, and waste reuse, offering to local consumers and communities electricity at a cost below retail prices. The emergence of the prosumer, a citizen capable of producing and consuming electrical energy, further contributes to decentralization. Prosumers can buy and sell electricity to the primary grid individually or as part of a local energy community. The evolution of new business models focusing on shared asset ownership, renting, and robust financial and regulatory frameworks is crucial in ensuring energy equity and resilience, especially for vulnerable consumers facing variations (and high increases) in electricity prices (Cong et al., 2022).

Digitalization, a driving force behind these transformations, was initially driven by deploying smart meters. However, recent advancements in internet-of-things and cloud technology are expanding digitalization beyond the electrical infrastructure to encompass grid users and service providers, including those from related sectors like mobility. Concepts like digital twins, energy data spaces, and the internet-of-energy are emerging, with several pilot projects currently in progress, meaning a shift towards a more connected and intelligent energy landscape (Monti et al., 2023).

In this context, modern AI technology can bring value in different dimensions:

- Fast decision-making in operating and planning power systems with high shares of RES, where the full use of flexibility from various sources (generation, consumers, or grid assets) is fundamental. This is especially crucial under challenging scenarios, such as extreme weather events and cyberattacks, where the system's adaptability becomes instrumental in maintaining infrastructure/system integrity and resilience.
- Enable the optimal operation of new decentralized business models, such as energy sharing between prosumers, smart electric vehicles (EV) charging, and de-risk energy

efficiency actions. This will contribute to democratizing access to RES at an affordable cost.

- Systematically process, explore, and exploit large volumes of heterogeneous data spanning the entire energy value chain and beyond, encompassing mobility, water, and high-performance computing domains. It can enhance and potentially automate existing (or new) tasks and processes traditionally handled by humans or expert systems that have new requirements like adaptability and robustness to new scenarios.

2.2 Application of AI

The European Commission (EC) White Paper on "*Artificial Intelligence: a European approach to excellence and trust*" (European Commission, 2020) describes how a regulatory framework for AI in the European Union (EU) could be developed and classifies the energy sector (among others like healthcare and transport) as high-risk sectors. Due to this high risk, this sector has been using expert systems as the core AI technology due to a) its structured and organized way of representing and storing expert knowledge, b) consistent decision-making, i.e., by applying the same rules and knowledge to similar situations, and c) the possibility documenting and transferring expert knowledge. One of the first state-of-the-art reviews was published in 1989, framing AI under the name "expert systems" (Zhang et al., 1989), and several expert systems (ES) used in the electricity power system were also reviewed in (Madan and Bollinger, 1997). Nowadays, ES is still available in commercial products and grid automation, e.g., grid protection systems and restoration (Kalra, 1988), and is still an active area of research in energy (Srivastava and Butler-Purry, 2006; Yang et al., 2022; Pruvost et al., 2023). Examples of industry success cases with ES are the online assistant, called SPARSE, to the operators of Substation Control Centers of the Portuguese Transmission System Operator (TSO) for intelligent alarm processing and advising regarding operator actions (Vale and Moura, 1993); and the online transient stability analysis system at the B.C. Hydro control center (Demaree et al., 1994).

The demand for adaptable solutions capable of learning from data (i.e., gathered from field sources or employing traditional physics-driven software tools for energy system simulation) increased significantly with the expansion of power systems and the integration of new energy sources. This motivated research in Artificial Neural Networks (ANN) and other machine learning (ML) methodologies, including decision trees and fuzzy inference systems. Initially concentrated on power system operation, this research gained momentum as the 21st century began, broadening its scope to encompass emerging applications such as demand response, RES forecasting, battery storage optimization, and asset management (Kezunovic et al., 2020). Examples of cases of success in industry are the use of decision trees and ANN for dynamic security assessment in Hydro-Québec and BC Hydro power systems (Huang et al., 2002); the use of several ML models (e.g., ANN, gradient boosting trees) for short-term RES forecasting (Bessa et al., 2017); predict the distribution network faults that are likely to occur under the given circumstances and their respective repair durations based on historical data of past storms and actual fault occurrences during storms (Vähäkuopus et al., 2019); or, a data-driven system that provides personalized Energy Efficiency (EE) recommendations for commercial customers and uses association rule learning to discover EE adoption patterns, i.e., relationships between various customer characteristics and EE products (Zawadzki et al., 2016).

Recent breakthroughs in AI research have led to a reinforced use of this technology within the energy sector, such as increased performance and decreasing costs of hardware, advances in deep learning for different areas such as computer vision or natural language processing (NLP), new paradigms such as transfer learning and generative AI, automated and low-code AI platforms, and brain-inspired new AI concepts (Hassabis et al., 2017). Moreover, industry-driven challenges, exemplified by L2RPN (Learning to Run a Power Network) from RTE, have prompted collaboration among AI scientists and power system specialists (Marot et al., 2021). These collaborative efforts motivated different groups towards the development of a new reinforcement learning-based assistant for aiding human operators in operating electrical grids during normal operation and when the system is under stress due to overloads or disturbances. A similar industry-driven approach is being followed by the AI4REALNET (AI for REAL-world NETwork operation) project, where AI-friendly digital environments for power grids, railway, and air traffic management are being developed to boost the development and validation of new AI techniques.

Two other emerging paradigms in the energy sector are physics-informed ML and edge intelligence. In problems where the numerical analysis approaches are complex to design, or too expensive to compute accurately, ML techniques are being used to solve algebraic equations or handle scenarios with limited data directly. For instance, the work of (Stiasny and Chatzivasileiadis, 2023) applies physics-informed ANN for time domain simulations of the power system dynamic response to load disturbances. The need to control locally distributed energy resources or microgrids, or concerns with energy-intensive computing and data privacy/security, motivates the research in edge AI for energy systems (Himeur et al., 2023).

To conclude, different energy sector stakeholders are putting their attention in AI technology, namely electricity system operators (TSO, Distribution System Operator – DSO), energy retailers, energy services companies, consumers/prosumers, communities, software, and automation vendors, among others, with the following main drivers for AI adoption:

- The ongoing structural transitions of electricity systems to accommodate many diversified and distributed energy resources, such as RES power plants, energy storage, and EVs. For instance, addressing challenges like RES variability and forecast uncertainty demands the creation of innovative tools for energy system operating. This includes the refinement of load and RES forecasting methodologies and the creation of novel tools designed to enhance human real-time decision-making processes.
- The evolution of electricity markets with increasing market actors and services diversification. Planning under these changes can be facilitated through new digital technologies. For instance, AI helps achieve the required decision-making automation in emerging local energy communities, e.g., in peer-to-peer trading.
- New challenges to system resilience (e.g., considering climate change and man-made hazards like cyber-attacks) could be mitigated through the integration of different data sources and the use of digital technologies. For instance, AI can augment policymakers' analytical capabilities, e.g., derive interpretable rules to explain energy scarcity events (Heymann et al., 2022).
- Increasing potential to analyze and optimize electricity demand patterns on the consumer side, e.g., through smart meters, controllable devices, and building sensors. AI can create socially relevant products, such as energy poverty forecasting or energy efficiency recommendation systems. It can also reduce energy costs and/or provide grid flexibility.

2.3 AI challenges

As mentioned in Section 2.22.2, energy is a high-risk sector. Therefore, aspects such as explainability and interpretability of AI-based systems are becoming fundamental requirements for AI adoption by industry (Heymann et al., 2023). In terms of challenges, this means:

- The **Human-centric AI** research should cover inherently interpretable AI models where humans can understand the mechanism that transforms input to outputs and modify it when the system behaviour is distant from the expected one.
- When not possible, explainability (e.g., leveraging from the Shapley values formalism) should be available to understand better and trust the model and support the model designer in improving its performance. For instance, in use cases like energy time series forecasting, more critical than model explainability is to have the capacity to understand which features are relevant to improve the forecasting skill.

Since energy systems, particularly the electrical infrastructure, are traditionally operated by humans, research in **Human-centric AI** should produce solutions that enhance human-machine collaboration and user experience. For instance, the seminal work *"Ironies of artificial intelligence"* (Endsley, 2023) identified the need to develop AI systems with "self-awareness" where the AI system can detect and inform situations that are outside of its boundaries of operations. In one L2RPN competition (Marot et al., 2022), RTE and TenneT (TSOs) integrated an additional term in the score function that measures the capacity of the AI agent to send alarms when it is self-aware of the "incapacity" to solve a specific problem and informs the human operator.

As also mentioned in Section 2.12.2, one fundamental limitation of ES adopted by industry was the difficulties in learning automatically from new data and operating conditions (e.g., modified by the presence of RES). Therefore, the dynamic nature of energy systems requires **Adaptive AI** systems that can adapt (online) to changing conditions, uncertainty (e.g., from RES), new data, and, if possible, human feedback.

The energy consumption associated with AI solutions demanding extensive computing resources is a significant concern for two sectors—energy and high-performance computing—both actively advocating for complete decarbonization and rational electricity use (Silva et al., 2024). Notably, the industrial deployment of large language models or reinforcement learning within real energy systems requires substantial computational resources, leading to increased energy consumption, at least during the training phase. This underscores the importance of embracing **Green AI** approaches. Additionally, as discussed in Section 2.22.2, the rise of edge intelligence (centralized, distributed, and decentralized monitoring and control architectures will coexist) for energy system control represents an emerging paradigm. In this context, optimizing local resources with **Green AI** is also essential.

Data privacy and security are also primary requirements for AI since, in various use cases, personal data (e.g., energy consumption, in-door sensors, outage events) or confidential data about the network infrastructure or electricity market trading are used. Therefore, research in **Trustworthy AI** should create solutions robust to data (model input and output) breaches and where reliability and security of the AI model are paramount. Certification and formal verification of AI models that operate autonomously or provide recommendations to humans is essential to guarantee trust, but also require standardized methodologies such as ISO/IEC 24029-2 *"Artificial intelligence (AI) — Assessment of the robustness of* *neural networks — Part 2: Methodology for the use of formal methods"*.

2.4 Use Cases Identification

The use case (UC) identification was made via a series of online workshop sessions organized between the industrial and academic partners of the Energy Vertical of ENFIELD, which aimed to conduct a first assessment of the project and the industry's goals.

This allowed us to identify the potential benefits and/or consequences on different stakeholders of AI-based solutions and first identification of the research challenges for the WP2 Pillars. The critical question was to evaluate to what extent AI would bring value to the smart energy system ecosystem. Moreover, to ensure coherence with the ENFIELD Description of Action (DoA), the list of use cases in Section 1.2.2 of the DoA was used as a starting point for the workshops discussions.

The outcome was a list of the first UCs for ENFIELD (summarized in TABLE 1) that will be used to foster the discussion with WP2 (the mapping between the use cases and the WP2 Pillars is presented in TABLE 2), conduct research internally in WP3, and the definition of the TES and TIS Open Calls in WP5. Important criteria to select these use cases were: i) relevance of the AI challenges for the WP2 Pillars, ii) data and/or infrastructure availability for AI testing and validation, iii) industrial partners strategic interest, and iv) potential to impact sustainable development goals, such as integration of RES and affordable energy.

Use case title	Where will be addressed?	Available data	Available infrastructure	Partners
UC1. Power system dynamic security assessment and maintain frequency stability	Internal	More than 500 operating scenarios were generated for Madeira Island's electric power system.	The digital environment developed in DIgSILENT software can generate synthetic data for AI methods.	INESC TEC
UC2. Load balancing in hybrid energy storage	Internal (INESC TEC, ISKRA), TIS (ISKRA)	Generated via simulation.	The digital environment is developed in Python and MATLAB Simulink software with the capacity to generate synthetic data for AI methods.	INESC TEC, ISKRA
UC3. Adaptive protection systems in electrical grids with distributed generation	TIS, TES	It can be generated on demand using the available infrastructure at INESC TEC. The open-source AI-friendly digital environment PyProD for protection analytics in distribution grids can generate data and test AI.	Smart-Grids and Electric Vehicles Laboratory (SGEVL) with two configurable physical microgrids, which can be extended to the virtual domain using a Power-Hardware-in-the-Loop setup based on an OPAL real-time digital simulator. Active protection architectures can be tested using the existing PHIL setup, but plans are set to equip the infrastructure with an active protection architecture.	INESC TEC
UC4. Coordinated edge control of electric vehicles charging at low voltage grid (or microgrids)	Internal (ISKRA), TIS, TES	6 months of EV charging sessions from commercial and built-in-house EV chargers.	EV charging infrastructure with 10 commercial chargers and 6 built-in-house EV charging prototypes with edge computing capabilities.	INESC TEC
UC5. Energy poverty prediction	TIS	Approximately one year of energy consumption data in the Municipality of Maia, Portugal; > 200 homes	Smart metering infrastructure in a neighborhood of apartments owned by the municipality.	CNET
UC6. Data authenticity and reliability validation	Internal, if not, TIS	Smart meter data from the ISKRA plant. Generic Renewable production data from more than one year and more than 10 wind farms in Portugal can be used for production forecasting models, but they will be distorted.	Smart meter infrastructure from ISKRA plant Historic wind farm data in the repository.	ISKRA, CNET,
UC7. Combine AI with LLM for clear human interaction with complex data	Internal within consortium, if not, TES	Smart meter data from ISKRA plant	Smart meter infrastructure from ISKRA plant Smart meter infrastructure from a large retailer and AMI from DSO are possibilities (to be confirmed).	ISKRA
UC8. Defining physical parameters of the electrical grid	TIS	AMI data from DSO (pending confirmation)	AMI from DSO (pending confirmation)	ISKRA
UC9. Smart management of an electrical factory (ship micro-grids)	TES, TIS	Historical data on microgrids about ship navigation scenarios.	KASEM platform to integrate IA-based solutions for data visualization and data analysis.	PREDICT
UC10. Energy-efficient production scheduling at the production process	TIS or Internal	~ 6k data ingestion per day on energy metrics in three machines. Historical data from > 8 months	MAGGIOLI MIRA platform for Digital Twins modelling and operations monitoring. Modelling assets (machines) and operations (processes) as DTs and performing analytics on top of each DT	MAG
UC11. Energy requirement to achieve thermal comfort conditions for occupants	TIS	Energy meters installed in MAG premises. Further meters to be acquired.	MIRA platform for Digital Twins modelling and operations monitoring. We will create a building DT (building logbook) in different granularities: Rooms and building as a network of rooms. MIRA will act as an aggregator of the data sources and will operate the thermal comfort service on top of each DT level	MAG
UC12. City sustainability index	TIS	City data from existing Maggioli Autosc@n installations, environmental sensors installed in city clients of MAG in Italy	MIRA platform for Digital Twins modelling and operations monitoring. We will create a city-DT and MIRA will act as aggregator of the data sources and will operate the index service on top of the digital Twin city	MAG
UC13. Methods of Explainable Machine Learning applied to LiDAR Scan Analysis	TES	SemanticKITTI dataset, S3DIS dataset, NuScenes dataset, PartNet dataset, EDP LABELEC overhead lines LiDAR dataset	HPC server at FCT NOVA	CNET
UC14. AI/ML implementation for demand forecasting	TIS	Smart metering data at building/ consumer data (or at sub-station level) and (if available) data from charging stations. Also, external data like weather data, energy market data.	The digital environment is to be proposed/developed, involving at a minimum a data management component (for real-time data handling) and the analytics engine for training and executing the ML models	MAG

Table 1 – Energy vertical use cases summary

WP2 Pillar	Challenges	Keywords	Energy vertical use cases
Green AI	Advancing Green AI on the Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Quantization and Pruning; Hardware Aware Architecture Search; On-Device Learning; Continual Learning (CL)	UC: 5, 6, 7, 8, 9, 10, 13
	Optimizing Green AI in the Edge-to-Cloud Continuum	Distributed AI; Edge-to-Cloud Orchestration; Lifecycle Assessment (LCA); Hybrid AI Models; Continual Learning Adaptation.	UC: 2, 4, 6, 7, 8, 10, 13
	Green AI Metrics Initiative	Standardization of Green-AI Metrics; Energy-Efficient Architectures; Lifecycle Environmental Impact; Computational Efficiency; Cross-Disciplinary Collaboration.	UC: 4, 6, 7, 8, 9, 10
Adaptive AI	Approaches to Incremental Learning Robustness and Trustworthiness	Incremental learning; Evolving systems; Concept drifts; Change adaptation; Robustness and Trust	UC: 3, 4, 9, 12, 14
	Advancing Adaptive AI on The Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Continual Learning (CL); On-Device Learning; Hardware-aware AI compression; Adaptive Deep Reinforcement Learning.	UC: 2, 3, 9
	Neuroscience-Inspired Adaptive AI	Continual Learning, Lifelong Learning, Brain-Inspired AI, Multimodal Learning, Sparsity	
Human-centric AI	Evolving Symbolic Models for Decision-Making	Symbolic AI; Reinforcement learning; Learning; Data-driven; Evolving.	UC: 1, 2
	Novel Explainable AI Methods for Decision-Making	Explainability; Spatio-temporal Models; Decision making; Healthcare	UC: 5, 6, 7, 10, 12, 13, 14
	Interpretable Data-Driven Decision Support Systems	Interpretable decision making; Automatic decisions; Collaborative human decisions; Integrated collaborated environment; Medical domain	UC: 5, 6, 10, 11
Trustworthy AI	Modeling Trust in Distributed AI System Architectures	Trustworthy AI; Distributed Systems; Trust Modelling; Software Architecture; Method Engineering	UC: 2, 4, 5, 6, 9, 10
	Detection of AI-Generated Content	AI content; Generative AI; LLM; Trust; Big data	UC: 7, 9
	Secure Voice Biometrics with Fake Voice Detection	Voice spoofing; Biometric security; Speech signal processing; Robust authentication; Acoustic analysis	

Table 2 – Mapping between the Energy vertical and the WP2 pillars

The following tables briefly describe each use case, covering the following aspects: a) industry challenge, b) state-of-the-art, c) expected impacts and outcomes, and iv) AI requirements. This list will be further revised in the next months with the WP2-WP3 co-creation workshops.

UC1_Energy. Power system dynamic security assessment and maintain frequency stability
Partners: INESC TEC (RTO)
Description: The scope of the UC is Dynamic Security Assessment (DSA), which refers to the continuous, real-time evaluation and monitoring of the stability and security of an electrical power system as it operates under dynamic conditions. It involves the analysis of transient and dynamic behaviors, such as disturbances, faults, or sudden changes in the system, to assess the system's ability to maintain stable and secure operation. DSA tools should provide human operators with timely information and actionable insights to prevent or mitigate potential disturbances and ensure the reliable and secure operation of the electric grid. The goal is to develop a data-driven inherently interpretable symbolic model for online (or real-time) dynamic security assessment (DSA) and to support human operators' definition of preventive actions in control rooms. The AI system will be an expert system that can integrate domain knowledge from human operators in the design and training phases, capable of learning (and evolving) from data.   **Industry challenge:** The integration of RES on a large scale prompts a transformation in the power system in a context characterized by reduced system inertia, higher generation and load variability, and a growing number of distributed energy resources. Within control rooms, this

transformation amplifies the monitoring and supervision requirements for human operators, limiting their task of ensuring the secure and reliable operation of the power system. The challenges introduced by RES integration are exemplified in the online DSA, namely: i) security classification becomes more complex due to the system's exposure to instability (low inertia) and the increased presence of DER with behavior conditioned by its primary source (e.g., wind, solar) and control methods, and ii) high number of scenarios requiring online evaluation due to RES variability and uncertainty. This complexity, coupled with the high presence of power electronics devices modeled by multiple differential equations, makes the online DSA too complex to be solved with conventional model-based techniques. Furthermore, this represents additional stress and a need for faster decision-making from human operators during unstable operating scenarios.

State-of-the-art: For this UC, the first approach of AI in the industry was the ES, where programming logic (e.g., Prolog) combines rules defined by an expert to make decisions based on the power system state (Zhang et al., 1989). The limitations of ES (as discussed in Section 2.2) motivated hybrid approaches, combining an ES with decision trees (DT) or fuzzy inference systems to integrate knowledge acquired from data (Jeyasurya and Venkata, 1990). Despite these hybridization developments, ANN and DT become the standard approach in the literature for online DSA, and more complex structures such as convolutional ANN (Gupta et al., 2019) and Graph ANN (Huang et al., 2020) were recently proposed. Although ANNs typically show remarkable generalization capabilities, their interpretability presents inherent challenges for human operators that may lead to algorithm aversion. For this reason, DT is currently used by industry (Huang et al., 2002). Nevertheless, in large problems, the tree can overgrow and become complex for human global interpretation. Tree pruning or penalty functions can limit the complexity but at the cost of accuracy. To increase the operator's trust, techniques from explainable AI can be used, for instance, to identify feature importance and its impact on the model's output (meaning an additional model in the chain), or trees can be used as a "proxy" model to increase interpretability (Ren, et al., 2022). Finally, humans operate power networks and systems in real-time based on their mental models and heuristics. Given the aforementioned reasons, no effort to explain model decisions can beat an inherently interpretable model's effectiveness (Rudin, 2019). Such models, characterized by their symbolic and crisp nature, facilitate a straightforward comprehension of internal dynamics and offer the capability to provide explanations.

Expected impacts and outcomes: Improve system security, measured with the following key performance indicators (KPI): i) rate-of-change of frequency, ii) operational cost. One AI-based algorithm for human decision-making in dispatching resources can provide inertia to the power system.

AI requirements: AI models that 1) incorporate human domain knowledge in the design and/or learning phases, 2) exhibit low complexity (e.g., rule-based system), and 3) recommend decisions to human operators in real-time (fast decision-making).

UC2_Energy. Load balancing in hybrid energy storage
Partners: INESC TEC (RTO), ISKRA (Industry)
Description: The scope of the UC is real-time control of load balancing between hybrid energy storage technologies, where typically high-energy density energy (HEDE) storage technologies are adopted to supply loads with a slow dynamic response, and high-power density energy (HPDE) storage units are employed to serve loads with high and rapid power fluctuations. This hybridization can effectively meet the requirements of various dynamic response, energy, and power density. The AI-based controller should be capable of learning from data and avoid high

computational and communication requirements. It can be an augmented rule-based expert system or a fully data-driven model.

Industry challenge: Nowadays, battery energy storage systems (BESS) such as ion-lithium batteries or compressed air storage have low energy losses, relatively low costs, and a large energy density. Nevertheless, they show poor performance during sudden load/generation variations due to low power capacity and slow dynamic response and have a limited lifecycle. Hybridizing BEES with other storage technologies, such as supercapacitors (SC), can tackle these limitations: BEES is used for steady-state power balancing and SC for high-frequency power fluctuations. However, proper power management strategies are needed to reduce investment and operational costs.

State-of-the-art: The control strategies in hybrid storage systems can be divided into three types (Lin and Zamora, 2022): centralized, decentralized, and distributed. Examples of centralized approaches are the rule-based methods, generally adopted by industry due to their lower computational complexity and more seamlessness for real-time applications (Teleke et al., 2010); and the fuzzy logic control approaches that generate reference power, which is decomposed into average and transient power (Cabrane et al., 2017). The decentralized approach is essentially based on consensus optimization or multi-agent approaches where information is exchanged between neighboring agents to achieve the global control goal via a sparse communication network (Olfati-Saber et al., 2007). Fully decentralized approaches are mainly based on the droop control concept and design of a control structure to coordinate the different droop-based controllers (Lin et al., 2021); however, ANN-based controllers (using reinforcement learning) are starting to become an alternative to complex droop-based control loops, especially when combined with domain knowledge in power system control theory (Duan et al., 2019).

Expected impacts and outcomes: Fast frequency response control considering the state-of-charge (SoC) variation of the HPDE-type device. Prevents the HEDE and HPDE from SoC violation and avoidance of ultra-fast frequency response from HEDE. Improve the transient response of the hybrid system and the lifetime of HEDE. One AI-based algorithm for real-time load balancing in hybrid storage systems.

AI requirements: AI models that i) offer low computational complexity, ii) are understandable for humans (e.g., enable human-guided modification or certification). Moreover, fully distributed solutions can be considered as an alternative to centralized control and avoid control problems due to communication delays. Furthermore, the AI solution can handle three tasks: predicting energy consumption for a fixed timeframe, energy production for a fixed timeframe, and management of loads, hybrid energy storage, and energy producers based on the current state of the grid and the predictions.

UC3_Energy. Adaptive protection systems in electrical grids with distributed generation
Partners: INESC TEC (RTO)
Description: The scope of the UC is the capacity of AI, as a data-driven technology, to amplify the capabilities of protection systems, addressing the challenges introduced by the dynamic nature of distributed energy resources. The goal is to go beyond fixed rule-based settings but avoid disruptive solutions (i.e., that can generate algorithmic aversion to human experts), such as integrating black-box models like ANN. The AI solution should ensure that the protection system adapts to different and challenging operating conditions but remains interpretable and has physical meaning.

Industry challenge: The advent of distributed energy resources, commonly including decentralized renewable energy sources, electric vehicles, and energy storage, has ushered in a new era of complexities for traditional grid-edge functions, for instance, those related to protective systems. Notably, the proliferation of distributed renewable energy has disrupted the conventional notion of unidirectional power flow assumed in relay settings, consequently altering the fault current patterns recorded at the failure point and within the substation. Meanwhile, integrating electric vehicle chargers into the grid may introduce a novel challenge in the form of current spikes, often causing misinterpretation of fault occurrences and location.

State-of-the-art: Grid protection systems are operated with expert systems, i.e., predefined rules and parameters defined by domain knowledge, physical equations, and trial-error experiences. Regarding AI, supervised learning, namely ANN, has been used for the adaptive distance protection concept, with the focus on demonstrating the capability of ANN to estimate the general power system condition using local measurements, offering potential applications in various adaptive protection concepts (Jongepier and Van Der Sluis, 1997). More recently, deep learning techniques like convolution neural networks have also emerged to enhance the protection scheme's robustness against various faults and system parameter variations in a microgrid context (Hatata et al., 2022). Reinforcement learning is also another solution, e.g., a long-short-term-memory-based RL algorithm, to improve coordination among protective relays, surpassing traditional inverse time over-current relays in reliability and accuracy (Wu et al., 2022).

Expected impacts and outcomes: Improve the resilience and quality of supply in distribution grids with a high integration level of DER. Increase protection systems' adaptability and self-learning capabilities to new (and challenging) operating conditions.

AI requirements: AI models that i) offer low computational complexity, ii) are only based on data collected at the edge level (i.e., protection device), iii) are capable of continuous learning and adaption to new data and operating conditions, and iv) are interpretable to human supervisors since protection systems have been based on expert knowledge for decades.

UC4_Energy. Coordinated edge control of electric vehicles charging at low voltage grid (or microgrids)

Partners: INESC TEC (RTO), ISKRA (Industry)

Description: AI-based systems can improve battery and charging management, optimize charging of vehicles in times of high-RES electricity supply, and allow the use of car batteries as an energy storage option for the grid (including local communities), considering end-use made by EV owners. Nevertheless, edge AI can increase the cost of EV chargers due to higher computational demand, leading to large-scale centralized forecasting and optimization of EV charging with high electrical energy consumption. Thus, frugal ML and FL solutions can be a technological solution to enable distributed intelligence and control at the EV Supply Equipment (EVSE) level and enable new services for EV users.

Industry challenge: The simultaneous charging of multiple electric vehicles (EVs) can create technical problems in the low-voltage local grid that decrease its hosting capacity, potentially creating a bottleneck for the decarbonization of the mobility sector. Therefore, intelligent EV charging strategies are required to manage charging rates and schedules, leveraging, for instance, local data (from EVSE) data and considering grid operating conditions, electricity tariffs, and EV drivers' expectations.

State-of-the-art: Commercial EVSEs generally adopted standards (e.g., ISO 15118) that provide multiple use cases like secure communication and smart charging. However, the smart charging control is generally fully centralized due to higher computational demand when running functions at the edge (i.e., at the EVSE). In the literature, effort has been made to explore different computational architectures in different computational layers (edge, cloud, hybrid). For instance, Sun et al., 2020, proposed an EV charging behavior analysis scheme for 5G smart grids that incorporates a three-layer smart grid architecture with network slicing and edge computing alongside hybrid AI methods such as KNN classification and LSTM prediction for EV charging behavior; another approach is a distributed, multilayer edge cloud architecture for improving scalability and sustainability in mobile autonomous vehicular edges and fogs, which uses Q-learning to dynamically distribute energy resources based on real-time spatial-temporal energy demand and mobility patterns (Radenkovic and Huynh, 2020). Coordination between multiple EV charging points is also important to avoid technical problems in the electrical grid (or microgrid), and game-theoretic approaches can be used to ensure consensus (Chavhan et al., 2023). Forecasting EV consumption and charging requirements is fundamental, like the "traditional" electricity demand and renewable energy forecasting, but with the difference that multiple parameters need to be forecasted: charging demand, arrival and departure time, and charging power. Moreover, the number of charging sessions per charging point must also be forecasted. For this task, different ML techniques were proposed in the literature. For instance, in (Brinkel et al., 2023), the authors compare multivariate linear regression, random forests, ANN, k-NN) to forecast the parameters of a virtual battery that represents the aggregated charging requirements of an EV fleet. In another work, a bottom-up approach with random forests is proposed to derive day-ahead probabilistic aggregated EV load profiles from raw data of individual EVs (Gerossier et al., 2019).

Expected impacts and outcomes: Increase network hosting capacity of EVs (postponing network reinforcement) and promote the use of renewable energy for EV charging.

AI requirements: Frugal (or green) ML and federated learning solutions can be a technological solution to enable distributed intelligence and control at the EVSE level and new services for EV users. Ensuring data privacy and security is a fundamental requirement.

UC5_Energy. Energy Poverty Prediction

Partners: CNET (Energy Utility R&D Center)

Description: From a residential energy consumption dataset, one should identify whether the respective consumer is moving into a state of energy poverty. This prediction is important for Governments, Municipalities, and institutions supporting households to guarantee their economic sustainability and social dignity.

Industry challenge: Energy players, mainly regulators and electricity companies, are eager to find ways to fairly evaluate if consumers should or should not benefit from Social Tariffs as part of social welfare policies. Regressive AI models can easily help in the process, but for a wide and fair application, these models need to commit to Green, Human-Centric, and Trustworthy AI, as defined in ENFIELD.

State-of-the-art: Energy poverty occurs when a household must reduce its energy consumption to a degree that negatively impacts the inhabitants' health and wellbeing[1]. Its main causes are high proportion of household expenditure spent on energy and low energy performance of buildings and appliances. In the past, monitoring and evaluation indicators have focused largely on outputs, service delivery or dissemination. The indicators design evolved then to adequately assess the needs of beneficiaries and describe the living conditions of families and communities (Pachauri and Spreng, 2011). The subject increased importance and other perspectives from Sociology and Philosophy even, came into role highlighting the concept

1 Energy poverty. (n.d.). Energy.ec.europa.eu. https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumer-rights/energy-poverty_en

of injustice as close related to energy poverty (Sovacool and Dworkin, 2015). Recently, innovative approaches using AI techniques have been increasingly applied to Energy Poverty alleviation; yet, it was identified that there is not a high number of works that apply AI to Energy Poverty alleviation (considering this problem as a multidimensional phenomenon). It was found that ANN algorithms were the most used models for low-income, energy price, and poor energy efficiency characterizations. Support Vector Machines-based algorithms were the most popular AI method applied to energy consumption-related problems. Deep learning was the most popular technique for detecting energy billing irregularities and unpaid energy bills) (López Vargas et al., 2022). The data here available comes from EDP Group's retailer and is based on domestic energy consumption.

Expected impacts and outcomes: Implementing this use case will considerably help in economic planning, Social Aid, and Regulation of Energy prices. So, at the end of the project, a methodology including an AI model/algorithm should be available enabling institutions with modest computer resources to evaluate, from a historic consumption dataset, if the respective consumer is tending to a state of energy poverty.

AI requirements: Green AI algorithms should be applicable since they are to be used in several entities (Regulators, Utilities, Municipalities, NGOs, etc.) where low processing power is available. Privacy should always be respected, and social bias should be avoided, or the model will fail its trustworthy targets. Federated reinforcement learning may be applied to the case so that higher improvement rates may be accomplishable in less time while respecting a human-centric approach. A Data Space reference architecture approach is preferred to apply this use case, foster cross-contributions between government, municipalities, social institutions, building companies and others.

Use case 6_Energy. Data authenticity and reliability validation
Partners: EDP CNET (Energy Utility R&D Center), ISKRA (Industry)
Description: Modern electrical energy systems rely heavily on large amounts of metering and other data. Metering data presents the primary source of information for billing purposes, as well as more advanced features, such as demand and grid flexibility forecasting. (Smart) metering data is sent periodically to the utility company, which stores and processes this highly private data. Customers can, in theory, corrupt the metering data to lower their energy expenses. When done on a large scale, such actions can lead to faulty demand forecasts and, therefore, disturbances on the electrical grid, resulting in noticeable financial losses. On the other hand, corrupt, fraudulent, or poisoned metering data presents a critical limitation for expert systems and/or AI models, which base their outputs on the provided input data. The main goal of this UC is, therefore, to develop an AI-based framework for utility companies that will i) validate received meter data in terms of data corruption, ii) validate the correct functioning of (smart) meter devices, and iii) generate alerts at corruption, fraud or data poisoning events. **Industry challenge:** A utility company's most important source of information is energy meter data. Various electrical parameter values are gathered periodically from vast numbers of metering devices spread across multiple locations. The (smart) meter data plays a crucial role in customer billing and various forecasting processes. The latter are based on high-level expert systems and, more recently, on AI models and algorithms. Source data, used in both cases, billing and forecasting, could be corrupt and/or faked. To provide a high-quality service, both to energy consumers and producers, the utility company must have means of identifying bad data. Data authenticity, i.e., the validation of data sources, and reliability, i.e., the correct functioning of measurement/acquisition devices, are directly connected to (smart) meter functioning and present the base for healthy data generation. Various parties with ill intentions actively try to corrupt the original or inject poisonous data, which causes issues on different levels of scale. Therefore, the utility company must preprocess the source data before using it in billing

and modeling operations. Erroneous data can lead to huge losses, e.g., wrong hydro water flow forecast, or even safety risks, e.g., human error caused by wrong recommendation by the AI system. This topic falls under the Human-Centric AI (autonomous, transparent bad data alert generation), Trustworthy AI (source data integrity is crucial), and Green AI (some preprocessing could be conducted on smart meter Edge devices) pillars.

State-of-the-art: Topics related to (smart) meter data privacy, authenticity, poisoning, reliability, security, etc., are, due to the important nature of the industry, widely researched. Currently, most data poisoning detection algorithms rely on historical time series data, but other, more sophisticated methods based on machine learning and AI are also starting to emerge. Because smart meters are considered key technological enablers of the smart grid, which could enable new sophisticated billing schemes and facilitate more efficient power distribution system operation, data privacy is a key concern (Muhammad Rizwan Asghar, 2017). The authors provide a structured overview and research directions of security solutions and survey recent work on data collection security for three application areas: billing, operations and value-added services, such as demand response. The major objectives of cyberattacks, targeted towards utility companies and smart grids, are the loss of data privacy and the threat to human life. Authors (Mohamed S. Abdalzaher, 2022) claim that there are several real-world smart meter privacy implementations in literature but argue that further research and testing are needed to increase effectiveness and decrease implementation costs. Modern technology may effectively mitigate attack manipulations that affect smart meters to decrease the negative impacts on infrastructure and human life. Smart grids enhance flexibility and reliability in power transmission through two-way communication among grid entities. Unlawful aggregated data manipulation can seriously affect efficient and reliable power distribution. Therefore, it is extremely important to preserve metering data privacy by secure aggregation and to authenticate the aggregated results (Dongyoung Koo, 2017). Machine learning and AI can be applied effectively to smart grids to enhance various aspects of the system, from making intelligent decisions and responding to sudden changes in customer demand, and fluctuations in renewable energy production to detection and prevention of anomalous behaviour, intrusion, cyber-attacks, malicious activities and data authentication (Salahuddin Azad, 2019). False data attacks have exposed the smart grid systems to a large variety of security issues. The authors (Lei Cui, 2020) provide a comprehensive survey of advances in machine learning-based methods to detect this threat effectively. Similarly, the authors of (Mahmoud M. Badr, 2023) review several data-driven methods to detect electricity fraud, i.e., meter tempering. They study various supervised learning methods, e.g., deep neural networks, and unsupervised learning methods, e.g., clustering. Additionally, they investigate the preservation of customer privacy using encryption and federated learning. Smart meters and other smart devices work in unison in smart grids and are considered part of Industry 4.0. Reliability and security of communication and data present the main challenges to such systems. Therefore, analysing and monitoring smart meter output data and validating whether this data is real or fake are two of the most important tasks to attend (Mahmoud Elsisi, 2021). Various machine learning and AI methods can be utilized to tackle the presented tasks. Still, none of them offer a whole-rounded solution to smart meter data authentication, validation, and fraud/poisoning detection.

Expected impacts and outcomes: The expected outcomes of this UC are 1) an AI algorithm for data series to identify possible poisoning before data is delivered to the main algorithm and 2) an AI/ML-based method for reliably detecting corrupt, fraudulent, and erroneous smart meter data. The measured KPIs are 1) poisoned data detection success rate, 2) data authenticity detection success rate, and 3) detection of smart meter operation success rate.

AI requirements: Use of real-time and historical smart meter data with appropriate AI/ML algorithms, e.g., reinforcement learning and adversarial machine learning, with the goal of quickly converging on the detection of bad data on each of the different parts of the energy supply chain (generation, grid, and consumption). The developed algorithms should show the capacity to have context awareness of various aspects of data authenticity and reliability validation. These AI requirements are aligned with the Human-centric AI, Trustworthy AI, and Green AI pillars.

Use case 7_Energy. Combine AI with LLM for clear human interaction with complex data
Partners: ISKRA (Industry)
Description: The UC simplifies and clarifies the interpretability of complex, energy sector-related data. The Green Transition brings many new concepts to residential as well as industrial users, who will have to start working with, till now, unimportant data connected to energy generation and consumption. Understanding the values, their interconnection, and context will present an important factor in navigating the energy ecosystem. This task currently requires a domain expert, who has vast experience with handling smart meter data. The main goal of this UC is to research the possibilities of developing and to develop a two-level AI and LLM-based SW solution that will i) accept human prompts for interacting with data and present the data in an understandable and clear format and ii) use the human prompts to prepare necessary data processing algorithms to extract the required data from complex data pools. **Industry challenge:** Modern devices can be considered as data generators, either utilizing the generated data directly for their current tasks or storing the data for potential future use. Smart energy meters and other smart devices, e.g., heat pumps, EV chargers, PVs, and inverters, all fall into this category. Smart energy meters can generate a snapshot of most main electrical parameters periodically, down to a one-second interval, and standard AMI energy meters usually generate data at 15-minute intervals. This enormous amount of complex and, at first sight, uncorrelated smart meter and other smart device data is generated at multiple collection points. The data holds various information about the observed energy system but is usually hidden from direct interpretation. Finding patterns in this data pool and interpreting it, therefore, requires expert knowledge of energy systems and their real-world implementations. It is nearly impossible to query the data without deep domain knowledge and specifically developed statistics and AI SW tools. Extracting derivatives in the form of co-dependencies, correlation, and others from the source data requires additional knowledge of the data and the tools being used. The topic falls under the Green AI (some preprocessing could be conducted on smart meter Edge devices) and Human-centric AI (human prompt and understanding friendly interface) Pillars. **State-of-the-art:** Versatile AI-based algorithms and solutions for smart meter data interpretation are starting to emerge but are still narrowly oriented, i.e., focusing on a precisely defined problem. One such solution is addressing the big data analytics problem with its SMASH platform, which enables data storage, querying, analysis, and visualization of large data sets (Tom Wilcox, 2019). Interpretation and presentation of the overall data and the results, provided by AI and ML systems, are still locked to human domain experts who act as data interpreters and provide simplification and clarification. Tools based on large language models (LLM) can be applied to many different applications and can tackle various challenges, but one needs to be aware of their limitations (Muhammad Usman Hadi, 2023). Such tools have already been aimed towards energy and power systems. (Jiaqi Ruan, 2023) have studied potential security threats that follow the application of LLMs to power systems. There are various challenges in energy and power systems that can be addressed using LLMs. One example is the annotation of electrical data from intelligent terminals. Currently, this task is

done manually and is thus time-consuming and challenging. Authors (Mi Zhou, 2023) propose a new, LLM-based approach to classify time series electrical data, which largely alleviates the need for annotated data when adapting to new tasks. Their approach improves the classification performance with the strong in-context learning ability of LLMs. On the other hand, LLMs can also be successfully used to enable better decision-making for demand flexibility of the end user. The end user must receive not only accurate but also understandable and actionable electricity demand forecasts. Authors (Dilini Rajapaksha, 2022) developed a framework that generates guidance in the form of rule-based explanations for forecasting models, thus increasing the interpretability of data. When solving specific tasks, data scientists often have to develop purpose-made solutions that are tailored to both the dataset and the task. LLMs can be used to act as code compilers. SEED (Zui Chen, 2023) was developed to automatically generate domain-specific data curation solutions based on human-level descriptions of the task, input data, and expected output. It generates code, a small model, and data access modules. To our knowledge, no all-in-one solution exists to address the topic described in this UC.

Expected impacts and outcomes: Use a combination of LLM and AI to provide a simple and user-friendly interface that enables users to interact with complex, smart meter-generated data. The expected outcome is a two-tier SW solution. The high-level (LLM-based) is used to accept plain language queries and to transparently and clearly present the data provided from the low level. The low-level (AI-based) is based on code, which is adaptively generated from high-level prompts/queries and processes the input (smart meter) data. The measured KPIs are 1) user-friendliness index, 2) prompt context awareness, and 3) low-level code generation quality.

AI requirements: Use 1) high-level LLM to translate human-friendly prompts into 2) low-level AI algorithms that work on smart meter-generated data to produce the queried data. The results are delivered to the high-level LLM, which presents the data in a clear and easily understandable form to the user. The presented AI requirements are aligned with the Human-centric AI Pillar.

Use case 8_Energy. Define physical parameters of the electrical grid
Partners: ISKRA (Industry)
Description: The UC addresses the trending topic of low-voltage network observability and its limitation due to data transfer bottlenecks. Low-voltage network observability presents an important area within the Green transition as it encompasses many aspects of the electrical grid quality and state of operation. Currently, the dominating approaches to the topic consist of two parts, the measurement infrastructure, which comprises smart energy meters and power quality analyzers, and data analysis. The quality of this data analysis is a direct function of the received data quality and data delivery robustness. Therefore, the communication channel between the sensory devices and the backend application tasked with data analysis presents a significant bottleneck. The limitation of frequency and volume of data transfer often results in suboptimal insights into the low-voltage network. This data is often used as source data for digital twins, meaning the DT outputs can be hindered. Utility companies would benefit immensely from improvements related to increased data granularity. The goals of this UC are to i) utilize the edge processing capacity of metering devices by embedding a portion of the required analysis directly within them, and ii) to develop AI/ML based algorithms to achieve a more granular understanding of the network, including estimation of network topology, i.e. phases, feeder connections and short-circuit impedance estimation, and improved fault detection.

Industry challenge: Data represents one of the most important if not the most important asset in the energy distribution sector. Real-world information is being merged with digital twin simulation results to enhance observability and increase awareness of various changes and modifications to the grid, e.g., the addition of EV chargers, PV systems, weather effects, etc. Digital twins of the electrical grid provide a powerful tool to simulate and predict various scenarios, such as the effects of adding renewable energy sources to households. To produce meaningful outputs, digital twins require a consistent and robust flow of valid data from real-world sensory devices, mainly smart energy meters. Digital twins have to introduce certain simplifications to the otherwise complex grid model to enable reasonable calculation times. Short-circuit line impedance is one such example, where theoretical values are currently being input instead of real values. These theoretical values for the physical characteristics of the grid limit the digital twin precision, resulting in inconsistent simulation outcomes. One of the main challenges utility companies face is the insufficient frequency and volume of data transfer from measurement devices to the analysis environments. Transferring most of the analysis work from the backend to the measurement devices, i.e., smart meters, would significantly decrease the needed communication traffic between the devices and the backend and would increase data fidelity. Such a step would widen the spectrum of obtainable information about network topology and the network in general, as well as provide the means to identify power theft and high-impedance faults and estimate technical losses. The topic falls under the Green AI Pillar as it is focused on developing and implementing edge processing on smart energy meters.

State-of-the-art: Grid management as an umbrella term is gaining increased attention in the energy distribution community. Low-voltage network observability presents one of the hot topics. Research work in enhancing network observability has led to the emergence of several solutions currently available on the market, e.g. from the key players Itron and Landis+Gyr come Intelligent Connectivity and Gridstream solutions. These primarily rely on smart meter data for conducting analysis. Some companies differentiate themselves by integrating additional data sources, such as GIS, to their solutions, e.g. Plexigrids Ari and LV Insights from Siemens. All of these solutions are targeting the low-voltage grid with the goal of providing as much insight as possible through direct data processing as well as digital modelling in the form of digital twins. While these solutions offer a diverse set of features, they largely converge on a shared methodology of harnessing available smart meter data and conducting analyses based on it. None of these solutions tackle the absence of high-fidelity measurements with high time resolution. The concept of digital twins has been adopted as an important aspect in digital transformation of power systems but its adoption into the energy sector has been recent. One important use case for digital twin technology is grid connected microgrids and (Namita Kumari, 2023) provides a review of the technology's potential, challenges, and novelties. The Internet of Things (IoT) and more specifically, the Industrial Internet of Things (IIoT), became normalized expressions when talking about advances in sensing and communication technology in industry. This concept can be tightly connected to digital twin technology and applied to electrical power systems. The authors of (Diaa-Eldin A. Mansour, 2023) discuss the use of IoT and digital twin technology for effective energy management with applications in smart homes, buildings, grids and industries. In addition, the paper addresses the challenges and opportunities of applying IoT and digital grid technology to electrical power systems. One of the important tasks in low-voltage network observability is short-circuit line impedance estimation and its use in digital twins for more realistic simulation. Currently, existing digital twins are based on theoretical cable properties and are prone to human error data entry into GIS/databases. Data entry can often be erroneous or can result in missing values. Up to our knowledge, real-time calculation of physical characteristics of the grid based on measurements does not exist yet. Authors of (K.O.H. Pedersen, 2003) have investigated different methods for estimating short-circuit impedance in the power grid for various voltage levels and situations. Similarly, some research has also been focused on high-voltage cable modelling (Beibei Qu, 2022), which can also be applied to low-voltage cable modelling, but to a limited extent (Rémy Cleenwerck, 2022). In addition, high-fidelity data with high time resolution can be used for improved fault detection. Authors in (Laiz Souto, 2020) present a new statistical method for fault location and classification in power distribution networks with DER and variable loads. The method relies on impedance measurements to build a model of the network operating conditions.

Expected impacts and outcomes: The expected outcome of the UC are algorithms and methods to be applied to edge devices on smart energy meters to address the following issues: Using smart meter data to calculate physical grid short-circuit impedance, AI to detect grid faults, tempering and other anomaly detection, federated learning to improve and evaluate the short circuit impedance values constantly. The KPIs are 1) grid fault, tempering, and anomaly detection success rate and 2) correctness of calculated/estimated short-circuit impedance.

AI requirements: Use of 1) AI/ML and federated learning-based validation of the calculated impedance, 2) analysis and detection of bad and fraudulent connections, cable overloads, etc. The presented AI requirements are aligned with the Green AI Pillar.

Use case 9_Energy. Smart management of an electrical factory (ship micro-grids)

Partners: PREDICT (Industry)

Description: This UC aims to investigate innovative IA-based approaches to perform smart management of energy use in the next generation of ships. The work will focus on optimization processes when dealing with complex hybridization of energy resources (electric, hydrogen, fuel…), often used as a mix in modern ships. This may include improvements in the energy system modelling, new strategies for load sharing and load-shedding, and the optimization of energy storage strategies, and battery use.

Industry challenge: Electrical technologies are becoming increasingly popular in the transport sector. After the tremendous developments in the electric vehicle sector, these technologies start to rise for maritime transport, as they offer a promising solution for improving energy efficiency and reducing CO2 emissions. Thus, many ships are now equipped with variable-speed drives for loads, such as pumps, fans, thrusters, propellers, and so on, known as ship microgrids. Microgrids have the advantages of being flexible, environmentally friendly, and self-sufficient and can improve the power system performance metrics such as resiliency and reliability. However, the design and implementation of microgrids are always faced with different challenges, considering the uncertainties associated with loads and renewable energy resources (RERs), sudden load variations, energy management of several energy resources, etc. Therefore, it is necessary to employ rapid and accurate methods such as AI techniques to address these challenges and improve the MG's efficiency, stability, security, and reliability.

State-of-the-art: Fossil and renewable energy mix or decentral energy production at factories combining heat and power systems (CHP) as well as through photovoltaic systems (PV) and energy-oriented PPC (Production Planning and Control). The Energy Management System for collecting, processing, visualizing, and archiving energy data. Conventional methods include MINLP, MILP (Mixed Integer Non/linear Programming), and Fuzzy Logic. Multi-criteria optimization approaches gather data from all systems (machines, devices, manufacturing processes, engineering, logistics, etc.) and heuristic algorithms to minimize power generation costs and maximize the remaining useful life. Machine learning-based approaches were also investigated, such as RBF NN, RNN, MLP, or reinforcement learning, but all these methods were demonstrated in simulation contexts so far and should be tested in real applications to exhibit real benefits and outline some limitations.

Expected impacts and outcomes: Development of algorithms that are highly reliable, time-critical, and computationally not very complex. Terrestrial microgrids have similar requirements in terms of communications, and thus, similar methods developed for terrestrial microgrids can be adopted for ship microgrids. AI-based solutions to design, manufacture, develop, and operate new generations of industrial systems as efficiently, reliably, and durably as possible. An IA-based system to maintain the power balance, prevent blackouts, improve load sharing and load-shedding strategies, and maintain balance on the power grid by matching consumption on production and gas emission reduction. Autonomous, trustworthy AI agents for the growing number of edge devices with control capacity in electrical grids.   **AI requirements:** Green and Adaptative IA-based solution performing energy optimization and gas emission reduction (adjustment of power consumption, load shedding, batteries use optimization, peak load prediction, and management, etc.) leading to a digital twin representing physical assets and/or processes to predict the performance of systems such as MG based on gathered data. Trustworthy IA-based algorithm that integer data and inputs from different cyber and physical systems for a resilient cyber-physical system in MG due to the interdependency of power and other critical infrastructure such as communications and that ensure data integrity, confidentiality, secure platforms, and privacy-conscious analytics techniques for the safe exchange of sensitive data.

Use case 10_Energy. Energy-efficient production scheduling
Partners: MAG
Description: Create a generic Energy-efficient production scheduling model that will be tested at the Maggioli editorial production process.   **Industry challenge:** To create a digital twin of the machine and the production process of Maggioli editorial production line and align production plans with energy efficiency. The idea is to monitor the energy demand of the production process and its most consuming machines and align production plans with the least energy spending. The work will develop a predictive analytics algorithm for: a) predicting energy demand based on historical data (currently, we have energy sensors in three machines with ~ 6000 values per day in total), and b) identifying trends in machine performance (based on energy variations), which lead to cases of predictive maintenance or repair. We will combine data from production orders and energy.   **State-of-the-art:** Manufacturing is moving from traditional preventive to more predictive maintenance models. This ensures a more proactive approach to machine repair and improved capacity. It is known that when a machine is underperforming the energy used increases or deviating from the normal conditions. While the concepts of Industry 4.0 and DTs are making rapid inroads into the manufacturing sector, there are several aspects that to be incorporated, to strengthen the goal of optimal process operations. One such aspect is the cognitive manufacturing element, (Bonnaud Serge et al., 2019) where the process plants can learn from pattern recognition in historical data and adapt to changes in the process, simultaneously being able to predict unwanted events in the operation before they happen. The induction of cognitive capabilities into the digital twin concept led to the novel concept of Cognitive Digital Twin (CDT), augmenting the capability of DTs to self-organize and offer solutions to unpredicted behaviours with various implementations in scheduling (Eirinakis et al., 2022) and predictive maintenance (D'Amico et al., 2022).   **Expected impacts and outcomes:** Delivery of a generic model, which, with some adaptations, might also be reused in other industries. We will test this in the Maggioli production line with at least a vast amount of data from at least 6 months (> 800.000 values). This model will be

embedded in the MIRA digital twin platform offered by Maggioli as a separate module targeting the industrial sector. **AI requirements:** • Predictive analytics for energy forecasting. • Complex event detection for energy trends and machine performance. • Explainable AI with both embedded mechanism for learning, AI model statement about how it works and finally user feedback loops.

Use case 11_Energy. Energy requirement to achieve thermal comfort conditions for occupants
Partners: MAG
Description: To collect data from energy sensor in buildings areas and combine it with thermal comfort behavioural models. **Industry challenge:** There is a need to reduce energy spending in buildings. The case will be that we create the digital twin of the building, get data from sensors about HVAC operation, weather data, physical vs. electric lighting and identify energy usage trends. The idea is to test different scenarios to find how energy is spent (e.g., occupancy vs HVAC operation, physical vs electric lighting). **State-of-the-art:** Energy spending in buildings can be reduced with 2 ways: with full automation or by identifying the energy usage models and find cases for improvements. We will focus on identifying the energy wasted (the energy spent but not for the needs of the occupants) by combining scenarios of occupancy, HVAC operation, lighting vs. physical light, etc. Moreover, elevated initial costs associated with sustainable features hinder widespread adoption, while a lack of standardization across regulations and a shortage of skilled professionals contribute to complexities. Addressing occupant behaviour, ensuring long-term performance, seamless technology integration, and fostering ongoing innovation stand as crucial focal points (Ayarkwa, J et. al., 2022). By addressing these challenges, the trajectory of sustainable buildings can be elevated, fostering a future where environmental responsibility and energy efficiency converge seamlessly. In response to this, A digital building logbook is a proposal from the EC's directive on the '*energy performance buildings*' that provides clear requirements for new buildings and renovation of existing ones, paving the way for realising its Green Deal, a climate-neutral built environment in the next 30 years. **Expected impacts and outcomes:** to create a reference digital building logbook through our existing digital twin's solution and create reference AI models for understanding thermal comfort and occupants' behaviour, which will be further used in the smart cities market where our client municipalities can monitor their public buildings and further to scale it up to residential, campuses, etc. **AI requirements:** • Complex event detection and behavioural analytics on top of each topology digital twin. • Aggregation of each DT behavioural model at the level of building DT (network of topology DTs). • Explainable AI with both embedded mechanisms for learning, AI model statement about how it works, and finally, user feedback loops.

Use case 12_Energy. City sustainability index
Partners: MAG

Description: Cities need to be greener. Thus, they need to create a smart sustainability model which will get data from different sources, cleanse them and calculate sustainability indices from different aspects (energy, CO2, mobility, etc.).

Industry challenge: We will offer to use our MIRA digital twin platform to model the city as network of assets DTs, each one representing buildings, public spaces, etc. we will collect information from existing sources (e.g. AutoSc@n solution from Maggioli, light and CO2, NOx sensors from ATM company belonging to Maggioli) and will aggregate them into a city context thus understanding various energy and environmental cases:

- Neighbourhoods with high mobility and energy/ CO2 demand
- Patterns of city energy and CO2, NOx pollution
- Areas for improvement

State-of-the-art: Cities are struggling with compliance with sustainability and green targets. Sustainability is a main focus from policy of global and national initiatives. In line with the 17 Sustainability Development Goals (SDGs)[2] we have the EU Green Deal with specific actions and targets that organizations have to fulfil. In line with this, Environmental, Society and Governance (ESG) is also getting more attention to sustainability by optimizing assets (sustainable plants, equipment), resources (energy, water, etc.) leading to optimized cost, reputation (social, environmental credibility) and less regulatory and level interventions (Henisz Witold et al., 2019). In this context, cities need to assess their impact from different sustainability perspectives in order to promote quality of life and alignment with the ESG goals.

Expected impacts and outcomes: We will provide a proof-of-concept of this model used in 1 city installation (from MAG existing customers)

Improved monitoring of sustainability and ESG metrics Contribute to the EU Mission 100 for neutral cities by 2030 Improved decision making in detecting areas for greener interventions.

AI requirements:

- Root-cause model with metrics, on sustainability based on ESG and other related models for cities. Behavioural model to understand patterns of energy use and pollution based on data from mobility, energy, CO2 and NOx sensors.
- Prediction model calculating the expected Sustainability indices.
- Explainable AI with both embedded mechanism for learning, AI model statement about how it works and finally user feedback loops

Use case 13_Energy. Methods of Explainable Machine Learning applied to LiDAR Scan Analysis
Partners: EDP CNET (externals: EDP LABELEC, Portugal, Nova-FCT, Portugal and Univ. Milano, Italy)
Description: Critical infrastructures, such as electric overhead lines, are crucial to the economy and social stability of a country or even continent. Their efficient maintenance avoids supply interruptions and, thus, a negative impact on society. AI is helping predict failures in those assets, but it can also help predict external interference from surrounding elements (e.g., growing trees on overhead lines). This UC, related to a TES initiative, aims to have an understandable AI model that automatically identifies types of objects from a 3D point cloud. The model hence developed will be applied to LiDAR files, namely for entities managing critical infrastructures, helping to identify vegetation and other elements that may, in time, pose risks

[2] *Sustainable Development Goals*. (2015). https://www.undp.org/sustainable-development-goals

to operation. Replication of this model, if successful, will reduce the time between observation and maintenance action, alleviating human expertise analysis.

Industry challenge: Current AI models, like deep-learning CNN, are heavy on processing load and are not easily explainable, which limits their use from economic and reliability perspectives, respectively. So, from the view of ENFIELD's Trustworthy and Green AI pillars, a model that may be explainable and use fewer resources would meet end-users' expectations. SCENE-Net is an intrinsically interpretable 3D point cloud semantic segmentation framework identifying signature geometric shapes via group equivariant non-expansive operators (GENEOs), allowing fast training even with a small amount of data and robustness both to labelling noise and strong imbalance. We propose to use a SCENE-Net composed of just 11 trainable geometrical parameters (like the radius of a ball or the height of a Cylinder), reaching a Precision gain of 24% against a comparable CNN with more than 2000 uninterpretable parameters. We expect to reduce the training time on a regular laptop below 1 and half hour for 40 000 km of overhead lines and inference time to around 20ms.

State-of-the-art: Electrical grids' careful inspection an important and challenging problem. Often, it is based on LiDAR large-scale point clouds with high-point density (Lavado, 2022), no sparsity, and small object occlusion. The captured point clouds are quite extensive and mostly composed of arboreal areas, making the task of transparently detecting objects, such as power grid poles, hard. A plausible way to approach this problem is to employ 3D semantic segmentation methodologies. State-of-the-art represent 3D scenes as volumetric grids (Maturana and S. Scherer, 2015) and as 3D point clouds (Qi et al., 2017; Thomas et al., 2019). Volumetric methods allow for the use of global feature descriptors, such as 3D convolutions but are restricted in terms of resolution due to the cubic growth of computational complexity and memory footprint. They also introduce challenges to ML models, namely heterogeneous density, lack of structure, and permutation invariance. Most proposals are tailored to boost performance in urban settings, e.g., Semantic3D (Hackel **et al., 2017)**, SensatUrban (Hu et al., 2021) and SemanticKITTI (Behley et al., 2019), where data are sparse, objects are often occluded and may demonstrate anisotropy w.r.t. density – this is not the case of the challenge we propose to overcome.

Expected impacts and outcomes: Since this will appear on a TES, one expects the following impacts: 2 scientific publications, one in a conference and another one in a scientific journal. Software application for object automatic georeferencing and classification for industrial use. Green benchmark on energy used for processing and correspondent CO2 reduction compared to CNN.

AI requirements: The mentioned SCENE-Net will target the surrounding overhead electric lines.

Use case 14_Energy. AI/ML implementation for demand forecasting
Partners: MAG
Description: Knowledge extraction from distributed energy time series data to improve energy consumption predictability and develop data-driven services oriented to maximize energy efficiency and management. **Industry challenge:** The decentralization and decarbonization of power grids introduce significant challenges for their operational and resilient management due to the wealth of Distributed Energy Resources deployed across their edges. To ensure the resilient operation of grids, Network Operators need to rely on real-time consumption data streams from individual

consumers, buildings and distributed assets (e.g. EVs), available either at DER-level or substation level, so as to improve their demand forecasting capabilities and have a better understanding on the demand their grid will need to cover at different time horizons (15-min ahead, hour-ahead, day-ahead, 72 hours-ahead) and facilitate specific business needs that are linked with the DSO business and will need to be effectively linked to each pipeline. **State-of-the-art:** Existing industrial solutions for demand forecasting are mainly built to process and analyse batches of historical data addressing demand at the whole grid level. Considering that the power grid is under a rapid decentralization with distributed assets generating vast amounts of real-time data, new concepts involving real-time data handling, processing and seamless real-time channelling through AI/ML pipelines for the extraction of valuable insights and forecasts are needed to address the evolving operational complexity of the grid and the needs of network operators for fine-grained knowledge and demand predictions to evidently support decision-making for the efficient management of the grid. **Expected impacts and outcomes:** Delivery of alternative AI/ML implementation for demand forecasting at varying spatiotemporal granularity to facilitate and evidently support decision-making on the side of network operators for the flexible management of their grids. (Feed info to Use case 12). **AI requirements:** AI pipelines (models and algorithms) capable of delivering accurate forecasts across various timelines (from 15 min-ahead to 3 days-ahead, according to the minimum velocity of available data) complemented by a comprehensive dashboard offering digestible knowledge to network operators regarding anticipated demand at grid and substation level, together with additional views for comparative analyses of results and correlation created with external factors.

3 Healthcare vertical

3.1 Context and motivation

The healthcare industry has been experiencing a gradual integration of AI technologies into different aspects of medical procedures and diagnostics. The motivation behind researching AI applications in healthcare sits in the growing need for improving efficiency, accuracy, and patient outcomes within hospital settings. As healthcare systems face challenges such as rising costs, workforce shortages, and increasing patient volumes, there is a pressing demand for innovative solutions that can streamline processes and enhance clinical decision-making and increase the resiliency of the welfare structure, to avoid congested situations such as the ones experienced during COVID-19 pandemic.

The EC has recognized the potential of AI to transform healthcare delivery and has outlined guidelines aimed at fostering responsible AI adoption within the European Union. These guidelines emphasize the importance of ensuring patient safety, data privacy, and ethical considerations in the development and deployment of AI-driven healthcare solutions. Compliance with regulatory frameworks such as the General Data Protection Regulation (GDPR) is crucial to safeguard patient information and maintain trust in AI technologies, in particular given the fact that the healthcare sector is by its own nature dealing with extremely sensitive data, whose exploitation may from one hand efficiently feed the AI-based tools, from the other one could mine the trust of the citizenship in the welfare structure.

3.2 Application of AI

AI is being applied across various stages of healthcare procedures and diagnostics, revolutionizing traditional approaches and augmenting clinical capabilities. One notable application of AI is in diagnostic imaging, where machine learning algorithms analyze medical images such as X-rays, Magnetic Resonance Images (MRIs), and Computed Tomography (CT) scans to assist radiologists in detecting abnormalities and making accurate diagnoses. By automating image interpretation and flagging potential anomalies, AI-powered diagnostic systems can expedite the diagnostic process and improve diagnostic accuracy. Another prominent usage of AI tools and techniques sits in the monitoring of biometric signals from wearable devices, which, leveraging on clustering techniques, can detect abnormal statuses of the patient and raise alarms, allowing a prompt intervention and avoiding further pain to the patient.

In addition to diagnostics, AI can also be exploited in hospital workflows to optimize resource allocation, improve patient flow, and enhance operational efficiency. AI-driven predictive analytics models can forecast patient admission rates, predict disease outbreaks, and identify high-risk patients, enabling healthcare providers to allocate resources effectively and proactively intervene to prevent adverse outcomes. Furthermore, AI-powered clinical decision support systems provide healthcare professionals with evidence-based recommendations, treatment guidelines, and personalized care plans tailored to individual patient needs.

3.3 AI challenges

One of the primary challenges facing AI implementation in healthcare is the integration of these technologies into existing clinical workflows and electronic health record systems. Healthcare organizations must navigate interoperability issues, data standardization, and data privacy concerns to ensure seamless integration and interoperability between AI applications and existing healthcare infrastructure. This aspect is also relevant in retrieving crucial information about pharmacology and norms, which are usually unstructured and hard to navigate for the medical staff. Moreover, the ethical implications of AI in healthcare, including issues related to patient consent, transparency, and algorithmic bias, require careful consideration and strong adherence to norms and laws.

A further consideration sees AI algorithms trained on biased or incomplete datasets to introduce disparities in diagnoses and healthcare delivery, given the minor representation of ethnical minorities in healthcare related datasets. Adhering to ethical guidelines and regulatory frameworks is essential to mitigate these risks and ensure the responsible and equitable use of AI in healthcare. Hence, robust validation and rigorous testing are essential to ensure the reliability, accuracy, and generalizability of AI-driven healthcare solutions.

In conclusion, while AI holds notable promises for improving healthcare procedures and diagnostics, several obstacles must be addressed to exploit these tools without introducing harmful situations which would impact the entire patients' pool. By navigating regulatory frameworks, addressing ethical concerns, and overcoming technical hurdles, healthcare organizations can harness the power of AI to improve patient outcomes, enhance clinical decision-making, and transform healthcare delivery in a responsible and sustainable manner.

3.4 Use Cases Identification

The UC identification was made via online meetings sessions organized between the industrial and academic partners of the Healthcare Vertical of ENFIELD, which aimed at conducting a first assessment of the project and the industry's goals.

The outcome was a list of the first UCs for ENFIELD (summarized in TABLE 3) that is being exploited to foster the discussion with WP2 (the mapping between the use cases and the WP2 Pillars is presented in TABLE 4), conduct research internally in WP3, and the definition of the TES and TIS Open Calls in WP5. Important criteria to select these use cases were: i) relevance of the AI challenges for the WP2 Pillars, ii) data and/or infrastructure availability for AI testing and validation, iii) industrial partners strategic interest, and iv) potential to impact sustainable development goals, such as integration of RES and affordable energy.

Use case title	Where will be addressed?	Available data	Available infrastructure	Partners
UC1. AI-Powered remote patient monitoring	TIS	OA databases	Not required	MAG
UC2. AI-Powered data quality enhancement	TIS, TES	Datasets coming from previous research initiatives	Wearable devices	MAG
UC3. AI-Powered remote patient monitoring	TIS, TES	Datasets coming from previous research initiatives	Wearable devices	MAG
UC4. Explainable electrocardiography (ECG) signal segmentation and classification	Internal, TES	OA databases	Wearable devices	TUE
UC5. Digital twin for enhancing cybersecurity in healthcare	Internal, TIS, TES	Not required	Not required	NRS
UC6. Patient monitoring system	TIS	Not required	Not required	KNOW
UC7. Nonlinear direct effect estimation	TIS, TES	Not required	Not required	KNOW

Use case title	Where will be addressed?	Available data	Available infrastructure	Partners
UC8. HOT- Health Optimization Tool, pharmaceutical data exploration and decision-making	Internal, TIS	OA and commercial datasets	Not required	KNOW
UC9. Early detection of diabetic retinopathy	TIS, TES	Not required	Not required	KNOW
UC10. VR in pain management (for distraction)	Internal, TES	Not required	Wearable devices	KNOW
UC11. Readmissing risk production	Internal, TIS, TES	Not required	Not required	KNOW
UC12. Evidence-based research with LLM oracles and Visual Analytics	TIS, TES	OA datasets	Not required	KNOW
UC13. Mixed-reality based gamified assessments	TIS	Not required	Wearable devices	KNOW
UC14. Explainable prediction of the outcome performance for different clinical pathways	TIS, TES	OA datasets	Not required	TUE
UC15. Primary healthcare full-cycle patient support, ecosystem administration- and logistic-aware	Interna, TIS, TES	Not required	Not required	ICCS

TABLE 3– HEALTHCARE VERTICAL USE CASES SUMMARY.

WP2 Pillar	Challenges	Keywords	Healthcare vertical use cases
Green AI	Advancing Green AI on the Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Quantization and Pruning; Hardware Aware Architecture Search; On-Device Learning; Continual Learning (CL)	UC: 1, 2, 3
	Optimizing Green AI in the Edge-to-Cloud Continuum	Distributed AI; Edge-to-Cloud Orchestration; Lifecycle Assessment (LCA); Hybrid AI Models; Continual Learning Adaptation.	UC: 2, 3, 6
	Green AI Metrics Initiative	Standardization of Green-AI Metrics; Energy-Efficient Architectures; Lifecycle Environmental Impact; Computational Efficiency; Cross-Disciplinary Collaboration.	
Adaptive AI	Approaches to Incremental Learning Robustness and Trustworthiness	Incremental learning; Evolving systems; Concept drifts; Change adaptation; Robustness and Trust	UC: 11
	Advancing Adaptive AI on The Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Continual Learning (CL); On-Device Learning; Hardware-aware AI compression; Adaptive Deep Reinforcement Learning.	UC: 3
	Neuroscience-Inspired Adaptive AI	Continual Learning, Lifelong Learning, Brain-Inspired AI, Multimodal Learning, Sparsity	
Human-centric AI	Evolving Symbolic Models for Decision-Making	Symbolic AI; Reinforcement learning; Learning; Data-driven; Evolving.	UC: 4, 8, 10
	Novel Explainable AI Methods for Decision-Making	Explainability; Spatio-temporal Models; Decision making; Healthcare	UC: 1, 4, 6, 7, 9, 11, 13
	Interpretable Data-Driven Decision Support Systems	Interpretable decision making; Automatic decisions; Collaborative human decisions; Integrated collaborated environment; Medical domain	UC: 1, 4, 6, 7, 8, 9, 10, 11, 13, 14, 15
Trustworthy AI	Modeling Trust in Distributed AI System Architectures	Trustworthy AI; Distributed Systems; Trust Modelling; Software Architecture; Method Engineering	UC: 4, 5, 15
	Detection of AI-Generated Content	AI content; Generative AI; LLM; Trust; Big data	UC: 4, 5, 12, 15
	Secure Voice Biometrics with Fake Voice Detection	Voice spoofing; Biometric security; Speech signal processing; Robust authentication; Acoustic analysis	UC: 4, 5, 15

TABLE 4 - MAPPING BETWEEN HEALTHCARE VERTICAL AND THE WP2 PILLARS.

Use case 1_AI-Powered Remote Patient Monitoring
Partners: MAG
Description: The scope of the UC is the development and deployment of an AI-Powered Remote Patient Monitoring, able to supervise patients' conditions from biometric signals transduced by wearable devices, in particular for what concerns diseases related to heart-related conditions. **Industry challenge:** To early detect cardiac events or diabetic complications by analysing in real time the relevant vital signs in an AI-powered wearable device. **State-of-the-art:** Existing wearable devices use electrodes to measure the electrical activity of the heart and generate a single channel ECG that can diagnose atrial fibrillation. Furthermore, they use PPG for heartrate tracking. Access to the raw data is typically not feasible. **Expected impacts and outcomes:** A wearable device with real-time monitoring and embedded AI algorithms that timely detect cardiac events and promptly alert the patient and caregivers. **AI requirements:** Novel, device embedded AI algorithms, for detecting: 1. *Arrhythmias (incl. atrial fibrillation) 2. Heart Attack (Myocardial Infarction) 3. Angina Pectoris 4. Heart Failure 5. Cardiac Arrest 6. Heart Valve Disorders 7. Coronary Artery Disease (CAD) *primary focus

Use case 2_ AI-Powered Data Quality Enhancement
Partners: MAG
Description: Data-driven solutions generally leverages on labelled data (at least for supervised learning methods) to derive decisions and trigger warnings and actions. For what concerns the healthcare domain, these data present a biometric nature and are their labelling is strongly connected to the physiology and the context/environment of the person generating data (e.g., blood pressure in sleeping phase or during physical exercise). To ensure a correct data interpretation and a broader benefit of AI-powered health-related algorithms, measures to correctly interpret the data both in phase of training and execution of the algorithm are needed. **Industry challenge:** Building Context Awareness to put measurements into perspective and access the quality of the data. **State-of-the-art:** Existing solutions are typically limited to individual measurements to provide context instead of the fusion of different insights. **Expected impacts and outcomes:** Wearable combining multiple sensors and allows to fusion those to a context aware state that allows to annotate the measured values and quantify their quality. **AI requirements:** Novel, device embedded AI algorithms, for the fusion of multiple sensors and capable of detecting context.

Use case 3_ AI-Powered Remote Patient Monitoring
Partners: MAG

Description: Human psychological statuses have been widely demonstrated to have some somatic effects, which can be measured by biometric analysis to reconstruct a posteriori the status of the monitored individual. The early and effective detection of these deviations can trigger several benefits for the interaction of the person with the context (e.g., can lead to diminishing the workload until the status shifts to a normal mood again, accelerating the recovery).
Industry challenge: Early identification of individuals with abnormal behaviour such as depression, fatigue or stress
State-of-the-art: Current solutions consider only episodic sample instead of a continuous monitoring of behavioural patterns.
Expected impacts and outcomes: Wearable analysing vital parameters, environment parameters and motion to detect anomalies in behaviour.
AI requirements: Novel, device embedded AI algorithms for abnormally detection and classification of:
1. Depression
2. Fatigue
3. Stress
4. Rage/Anger

Use case 4_ Healthcare. Explainable electrocardiography (ECG) signal segmentation and classification

Partners: TUE

Description: The project focuses on developing a system for explainable electrocardiography (ECG) signal segmentation and classification. This involves the process of breaking down ECG signals into meaningful segments and accurately categorizing them based on diagnostic criteria.
Industry challenge: The interpretation of ECG signals, which serve as diagnostic criteria for various cardiopathies including rare diseases, can be challenging. Interpretations may vary between experts, leading to discrepancies in diagnoses.
State-of-the-art: Currently, on the clinical floor, decisions regarding ECG interpretations heavily rely on the expertise of healthcare professionals. However, considerable efforts have been made in the use of advanced methodologies aimed at enhancing diagnostic accuracy and interpretability. Deep learning models, particularly convolutional and recurrent neural networks, form the backbone of ECG interpretation, leveraging their ability to learn intricate patterns within ECG signals (Pyakillya et al., 2017), (Liu et al., 2021). Data augmentation techniques address challenges related to limited labeled data (Cao et al., 2020), while multi-task learning approaches enable simultaneous segmentation and classification tasks (Qiu et al., 2021). Notably, the emergence of explainable AI (XAI) emphasizes transparency and trust by providing human-interpretable explanations for model decisions. XAI techniques ensure healthcare professionals understand the rationale behind AI-generated diagnoses, fostering collaboration and consensus-building within medical teams (Jo et al., 2021), (Anand et al., 2022). This holistic approach promises to revolutionize ECG interpretation, advancing diagnostic accuracy, enabling early detection of cardiac abnormalities, and ultimately improving patient outcomes in clinical settings.
Expected impacts and outcomes: The expected impacts and outcomes of the project encompass a twofold approach aimed at revolutionizing ECG signal interpretation. Firstly, through the utilization of AI algorithms, the project seeks to significantly enhance diagnostic accuracy, thereby facilitating more precise diagnoses. Secondly, by implementing a system that provides explanations for its classifications, healthcare professionals will gain valuable insights into the rationale behind automated diagnoses, fostering transparency and trust. This transparency not only enhances interpretation but also facilitates consensus-building among experts, ultimately leading to more effective patient care. The primary metric for evaluating

success will be the improvement in diagnostic accuracy across diverse ECG signal types, serving as a key performance indicator (KPI) for the project's overall impact.

AI requirements:

- Explainable AI Models: The AI models developed must be explainable, meaning they can provide clear justifications for their predictions. This is crucial for gaining trust from healthcare professionals and ensuring transparency in the decision-making process.
- Incorporation of Expert Knowledge: The AI models should be trained using expert knowledge in the field of cardiology. This ensures that the system learns from the most relevant and accurate information available.
- Human-Validated Explanations: The explanations provided by the AI models should be validated by human experts to ensure their accuracy and relevance.

Use case 5_ Healthcare. Digital Twin for Enhancing Cybersecurity in Healthcare
Partners: NRS
Description: For their own nature, healthcare structures host sensitive data, which, if breached, can allow malicious agents to retrieve unfair advantage or to enable criminal practices like blackmailing. Enhancing Cybersecurity in Healthcare becomes hence a priority, in particular in a context characterised by the massive collection of biometric data and other sensitive information. **Industry challenge:** From the healthcare industry perspective, it is challenging to have a continuous overview of healthcare infrastructures and services to tackle cybersecurity threats and risks. **State-of-the-art:** Digital Twin offers significant advantages to cybersecurity experts, empowering them to predict risks without entering the physical world, and to simulate and test cyber-attacks that would otherwise be infeasible to do in the real-time physical environment. **Expected impacts and outcomes:** i) Improve the cybersecurity security in near real-time using NR platform, and ii) algorithm based on Digital twin technology for detecting and forecasting cyber threats using AI/ML **AI requirements:** AI models such as RNN and CNN were required a) to predict cyber threats and risks, and b) to be able to process, detect, and predict the events in physical twin and virtual twin

Use case 6_ Healthcare. Patient monitoring system
Partners: KNOW
Description: In the context of patient monitoring, the activities usually leverage on the design of a region of “normality” located in a hyperplane consistent of several parameters (with lower and upper bounds). These burdens which limit the physiological normality of a person’s status are however very subjective, as influenced by characteristics such as the gender and the clinical history of the patient. The flexibility of these burdens hence limits the exploitability of several data-driven applications, which need hence some additional tools to automatically re-derive the regions of normality to enable a proper execution of the monitoring functions. **Industry challenge:** Monitoring hospital wards is a time-consuming task. Patients have different characteristics and reference values for human physiological signals. **State-of-the-art:** Currently, human judgment and rule-based automated systems complement each other. **Expected impacts and outcomes:** Reduced number of false alarms (due to conservative thresholds), improved detection of slowly deteriorating health indicators, potentially personalized models for long-term patients. **AI requirements:** AI models that model patient states and detect anomalies/changes in an automated manner.

Use case 7_Healthcare. Nonlinear direct effect estimation
Partners: KNOW
Description: The huge variety of parameters characterising the human body response to medical treatment induces nonlinear effects in patients who undergo a clinical therapy, making hard to predict the effects of a treatment and the recovery time, as well as it can lead to several iterations with the specialist medical doctor in the attempt to refine the therapy. **Industry challenge:** In clinical studies, it is hard to distinguish the direct effect of a treatment on the outcome from the mediated/total effect (e.g., a treatment has an effect that itself affects the outcome). **State-of-the-art:** Currently, controlled trials are required, and direct effect estimation is easily done mostly for linear models. **Expected impacts and outcomes:** Methods for nonlinear direct effect estimation may potentially improve the trade-off between effort and significance of a clinical trial (reduced group sizes, etc.) **AI requirements:** Clearly described methodology.

Use case 8_ Healthcare. HOT- Health Optimization Tool, Pharmaceutical Data Exploration and Decision-Making
Partners: KNOW
Description: In the current scenario, utilizing new technology is essential for better data management, visualization, and decision-making. HOT (Health Optimization Tool) emerges as an innovative solution in the realm of pharmaceutical data exploration and decision-making, leading to time and effort reduction, and facilitating proactive enhancements in medical treatments. **Industry challenge:** Searching for information which is not easy to find due to missing data relations and no visualization options. **State-of-the-art:** Current pharmaceutical experts face challenges in efficient data exploration, decision-making, and lack of a unified data source. Existing tools may not fully harness AI capabilities for enhanced insights. **Expected impacts and outcomes:** Easy data filtering and clustering which leads to time and effort reduction. Easy finding of data relations and sparsity. Data management and visualization at ones. In-house search tool which can be used on different textual. Supporting in decision improvement like for example medical treatments. Preventing lack of a unique data source. **AI requirements:** • Customization Options: Provide an open configuration option for users to customize AI models based on their specific needs, allowing flexibility in adapting AI functionalities. • Data Security Measures: Implement robust security measures to protect sensitive pharmaceutical information processed by AI models, ensuring compliance with data protection regulations. • Continuous Improvement Mechanisms: Establish processes for continuous monitoring and improvement of AI models, incorporating user feedback and adapting to evolving data patterns and pharmaceutical research trends. • User-Friendly Interfaces: Design intuitive interfaces that seamlessly integrate AI-driven features into the HOT tool, maintaining a user-friendly experience for pharmaceutical experts.

Use case 9_Healthcare. Early detection of diabetic retinopathy
Partners: KNOW
Description: Current methods for diabetic retinopathy are resource-intensive and inaccessible in many regions. To this purpose, edge computing in medicine still has a lot of margin for improvement, enhancing activation functions for real-time diagnosis. The integration of these functions enables a reduction of time for results and facilitates a prompt intervention, potentially preventing vision loss. **Industry challenge:** Efficient and accurate identification of early signs of diabetic retinopathy (DR) among diabetic patients is a critical challenge in the healthcare industry. Timely detection is essential for preventing irreversible vision impairment. Current diagnostic methods may be resource-intensive and not readily available, particularly in regions with limited access to specialized medical infrastructure. **State-of-the-art:** Current diagnostic methods may be resource-intensive and not readily available, particularly in regions with limited access to specialized medical infrastructure. Recent advancements in deep learning models have shown promise in diabetic retinopathy diagnosis. However, most models are designed for deployment on high-end computational resources, limiting their accessibility. Edge computing in the medical field is an emerging area, but the integration of enhanced activation functions for real-time diagnosis on edge devices is a novel frontier. **Expected impacts and outcomes:** The integration of enhanced activation functions enables real-time diabetic retinopathy diagnosis on edge devices, reducing the time taken for results and facilitating prompt medical intervention. By leveraging edge computing, the diagnostic system becomes more accessible, particularly in regions with limited access to advanced medical infrastructure. This contributes to early detection and intervention, potentially preventing vision loss. The proposed activation functions are designed for computational efficiency, making them suitable for deployment on resource-constrained edge devices. This reduces the dependency on high-end computational resources. Faster and more accessible diagnosis can lead to improved patient outcomes by enabling timely and targeted medical interventions. This is especially critical in managing diabetic retinopathy, where early detection is key. **AI requirements:** • Develop and integrate activation functions that are not only effective for diabetic retinopathy diagnosis but also optimized for edge computing, considering factors such as latency, energy consumption, and model accuracy. • Design models and algorithms that can operate efficiently on edge devices, ensuring real-time processing and minimizing dependence on centralized computational resources. • Implement model compression techniques and quantization to create lightweight CNN models suitable for deployment on edge devices without compromising diagnostic accuracy. • Develop mechanisms for integrating real-world data into the diagnostic system, ensuring the robustness and relevance of the solution in diverse clinical scenarios. • Engage with healthcare professionals for clinical validation to ensure the reliability and accuracy of the diagnostic system. Incorporate feedback from the medical community in refining and improving the system.

Use case 10_Healthcare. VR in pain management (for distraction)
Partners: KNOW

Description: In healthcare, pain management presents challenges in providing effective and personalized relief. VR, coupled with AI algorithms, could offer immersive distractions from pain, as well as monitoring physiological responses for real-time adjustments. These adjustments potentially reduce reliance on medications, particularly in chronic pain cases, enhancing patient satisfaction.
Industry challenge: Pain management is a complex aspect of healthcare, with challenges in providing effective and personalized pain relief strategies. VR is used to create immersive and engaging environments that can distract patients from pain. AI algorithms continuously monitor patient responses, including physiological indicators (e.g., heart rate, skin conductance) and subjective feedback. The AI dynamically adjusts the VR experience in real-time based on the observed data.
State-of-the-art: Traditional methods often rely heavily on medications, and there is a need for innovative, non-pharmacological approaches to address pain, especially in chronic conditions.
Expected impacts and outcomes: AI-driven adjustments to the VR experience enable personalized pain management strategies tailored to each patient's responses.
By providing effective non-pharmacological interventions, this approach may contribute to reducing the reliance on pain medications, particularly in chronic pain cases.
Real-time optimization of the VR experience enhances patient satisfaction and engagement, contributing to a positive overall experience.
AI requirements:

- AI algorithms should be capable of monitoring patient responses in real-time, integrating data from various sensors and feedback mechanisms.
- The AI system needs to employ adaptive algorithms that can dynamically adjust the VR experience based on the changing needs and responses of the patient.
- Seamless integration with patient health records and historical data to understand individual pain profiles and preferences.
- AI algorithms must incorporate safety protocols to ensure that the adjusted VR experiences are within safe and comfortable parameters for each patient.
- The AI system should be able to analyse subjective feedback from patients, considering their reported levels of pain and comfort, to refine and improve the pain management strategy.

Use case 11_ Healthcare. Readmissing risk prediction

Partners: KNOW

Description: Hospital readmissions present significant challenges in healthcare, impacting patient outcomes, resource allocation, and costs. Early identification of high-risk patients enables personalized care plans, potentially reducing readmission rates.
Industry challenge: High rates of hospital readmissions pose challenges for healthcare providers in terms of patient outcomes, resource allocation, and overall healthcare costs. Identifying patients at risk of readmission and implementing proactive measures is a complex challenge.
State-of-the-art: Currently, it is hard to predict the likelihood of hospital readmission after discharge.
Expected impacts and outcomes: Early identification of high-risk patients allows for personalized care plans and interventions, potentially reducing the rate of readmissions.
Resource Optimization Healthcare providers can allocate resources more efficiently, directing additional support to patients who are at a higher risk of readmission.
Proactive interventions may lead to cost savings by preventing avoidable readmissions and optimizing the use of healthcare resources.
AI requirements:

- Comprehensive patient data from electronic health records (EHRs) and other relevant sources
- Capability of analysing complex datasets and learning patterns associated with readmission risk.
- The ability to process data in real-time is essential for timely risk assessments and intervention strategies.
- AI models should be interpretable to gain the trust of healthcare professionals, ensuring that predictions align with clinical understanding.

Implementing ethical practices and ensuring patient privacy and consent are vital aspects of deploying AI in healthcare.

Use case 12_Healthcare. Evidence-Based Research with LLM oracles and Visual Analytics
Partners: KNOW
Description: Current search interfaces require big efforts, and language models are not optimized for document searches. Enhancements in search capabilities can reduce time spent searching, allowing scientists to focus on analyzing and comparing clinical study outcomes. Assisted summarization with language models can help in the organization, enhancing communication and explanation of results. **Industry challenge:** Evidence-based research is a well-established process used to search for finding published scientific studies towards answering a clinical question. Identifying prior studies with and support evidence for clinical treatments requires exhaustive scanning through published literature. **State-of-the-art:** Currently available search interfaces demand enormous efforts to find and collate outcomes for each specific question. Language models are not tailored to search documents. **Expected impacts and outcomes:** Reduced time searching and increase time processing: Enable scientist to focus time on analysing and comparing outcomes of clinical studies by reducing the time needed to find precise information. Enhance their capabilities to understand and compare outcomes with comprehensive visualizations. Contextual updates: use specific models to find new evidence and update resources for past / current open clinical questions. Assisted summarisation: use support from language models to assist the organization of evidence for later presentation or as key input to dataset. **AI requirements:** • Customized Search Through Model Embeddings: use LLMs to build topical groups of embeddings to support search. Train and improve models to answer search questions with evidence. • Persistent contextual memory: train personalized models to store persistent memory of the interaction/conversation context. Incorporate ability to recall context and maintain longer dialogues without losing coherence. • Visual Analytics Pipeline: use visualization to communicate large quantities of information. Rely on visual analytics methods to provide input, annotations and requests to the model. Provide explainable language methods that can be presented visually.

Use case 13_ Healthcare. Mixed-Reality Based Gamified Assessments
Partners: KNOW

Description: Early detection is crucial for diseases like Parkinson's and Alzheimer's. Current methods often fail to achieve early detection. This project include pre-screening with gamified applications for early detection and continuous monitoring to support expert diagnoses.
Industry challenge: Assessments for various types of diseases are carried out at the clinic with specialized tests and/or equipment. This limits the capacity for early detection of diseases. Detection of early onset is critical for treatment of various diseases, from vestibular problems that cause falls, through Parkinson's and Alzheimer's disease.
State-of-the-art: Early detection of diseases is often not possible.
Expected impacts and outcomes: Early pre-screening of potential illnesses: use gamified applications with immersive technology to assess skills. Continuous monitoring of key skills to support expert diagnoses.
Early access to treatment: expert diagnosis based on comprehensive data collection with multiple sensors.
Improvement of life quality: due to access to early treatment.
AI requirements:

- AR/VR serious games for skills assessment: design and develop games that allow for continuous skills assessment towards understanding the development of degenerative diseases.
- Comprehensive patient data from electronic health records (EHRs) and other relevant sources
- Visual Analytics pipeline: provide visual tools to analyse and collate all patient information available.

Use case 14_ Healthcare. Explainable prediction of the outcome performance for different clinical pathways

Partners: TUE

Description: The project aims to develop an explainable prediction system capable of assessing the outcome performance across various clinical pathways. By focusing on palliative care, it addresses the critical need for personalized treatment strategies that consider the dynamic nature of patient characteristics and the varying efficacy of treatment combinations within clinical pathways.
Industry challenge: In palliative care, the utilization of different treatment combinations within clinical pathways can lead to varying patient outcomes. Furthermore, patient characteristics evolve over time, posing a challenge to traditional static prediction models used at the time of diagnosis. This necessitates the development of dynamic and adaptable predictive models to account for the changing nature of patient conditions.
State-of-the-art: Prognostic accuracy in palliative care is valued by patients, carers, and healthcare professionals. Previous reviews suggest clinicians are inaccurate at survival estimates but have only reported the accuracy of estimates on patients with a cancer diagnosis (White et al., 2016). Currently, static prediction models are used at the moment of diagnosis without considering the evolution of the patient (Sandham et al., 2022).
Expected impacts and outcomes: The project aims to achieve improved accuracy in predicting patient outcomes, particularly in terms of maximizing survival time. By developing an explainable algorithm for outcome prediction, the project seeks to provide valuable insights into the significance of treatment presence and position within clinical pathways. Additionally, the introduction of a prescriptive algorithm for pathway modification holds promise in optimizing treatment strategies and improving patient outcomes.
AI requirements: To address the complexities of predictive modelling in palliative care, the project requires advanced AI capabilities. Specifically, it necessitates the development of explainable AI models tailored for sequential decision-making. These models must effectively

incorporate additional patient information into the learning process and produce human-validated explanations for their predictions. This ensures transparency, reliability, and trustworthiness in the decision-making process.

Use case 15_Healthcare. Primary Healthcare Full-cycle Patient Support, Ecosystem Administration- and Logistics-aware
Partners: ICCS
Description: The challenge in the healthcare industry is to translate promising AI results in medical diagnosis, contrasting public scepticism. Collaborative ecosystems are crucial for this purpose, necessitating at the same time comprehensive training datasets and guidelines to navigate AI. One potential solutions entails initiating consultations with the patients employing audiovisual data, with the goal of improving process efficiency, facilitating referrals to specialists or examination rooms within the hospital. **Industry challenge:** The emergence of promising AI results in medical diagnosis contrasts with public scepticism. Can these results be replicated on a large scale? Ecosystems, which could encompass individual hospitals or even entire countries, are needed by this discussion. There is a pressing need for comprehensive training datasets and the establishment of guidelines to navigate the current and anticipated hype surrounding AI in healthcare. Collaboration is essential to avoid redundant efforts and promote efficiency across the board. **State-of-the-art:** The burden of primary healthcare weighs heavily on hospitals, as well as patients. Overwhelmed by long queues, patients frequently find themselves shuttled between various queues, leading to logistical challenges and administrative complexities. This system leaves patients feeling disempowered and frustrated. **Expected impacts and outcomes:** A proposed solution involves an initial consultation with the patient, thorough history-taking, and the utilization of sound recordings, images, or videos as necessary. Access to patient files aids in the formulation of initial risk assessments and facilitates appropriate referrals to specialist doctors or examination rooms within the hospital. This proof-of-concept approach aims to establish a framework and guidelines to streamline processes for all stakeholders involved. **AI requirements:** The successful implementation of AI in this context needs capabilities for natural language interaction, the administration of questionnaires, and the utilization of audiovisual sensors to capture and analyse near-real-time data. These sensors, including microphones and cameras, are instrumental in determining whether additional information is required. Furthermore, an initial roadmap for patient care and the optimization of internal scheduling within the healthcare ecosystem are key components of the AI requirements.

4 Manufacturing vertical

4.1 Context and motivation

The landscape of manufacturing is undergoing a deep evolution with the integration of AI technologies, guided not only by the pursuit of efficiency and productivity, but also by the principles of "trustworthy AI," "green AI," "human-centric AI," and "adaptive AI." These principles, as outlined by the European Commission, serve as pillars for the ethical, sustainable, and human-centered deployment of AI in manufacturing processes.

Trustworthy AI embodies the need for AI systems to be transparent, accountable, and fair. In the manufacturing sector, this translates into ensuring that AI algorithms are explainable and unbiased, thus fostering trust among stakeholders. Manufacturers are increasingly prioritizing the development of AI systems that adhere to ethical guidelines and regulatory frameworks, such as the GDPR, to safeguard data privacy and mitigate the risks of algorithmic discrimination, also with respect to the recent changes occurring in production environment, given the so-called “Industry 5.0” and the consequent deeper involvement of human actors in interactions with AI tools.

Green AI emphasizes the importance of environmental sustainability in AI development and deployment. In manufacturing, AI-driven optimization algorithms are utilized to minimize energy consumption, reduce waste, and optimize resource utilization across the production lifecycle. By leveraging AI technologies for energy-efficient manufacturing processes, companies can mitigate their environmental footprint while simultaneously enhancing operational efficiency and cost-effectiveness.

Human-centric AI underscores the significance of designing AI systems that prioritize human well-being, safety, and autonomy. In the manufacturing context, this involves the collaborative integration of AI-powered robotic systems alongside human workers to enhance workplace safety, ergonomics, and job satisfaction. Moreover, AI-enabled assistive technologies support workers in performing complex tasks more efficiently, fostering a symbiotic relationship between humans and machines.

Adaptive AI encompasses the capacity of AI systems to continuously learn, evolve, and adapt to changing contexts and requirements. In manufacturing, adaptive AI algorithms enable real-time optimization of production processes, predictive maintenance, and quality control, thereby enhancing agility and responsiveness in dynamic environments. By harnessing the capabilities of adaptive AI, manufacturers can effectively navigate uncertainties and disruptions while maintaining operational resilience and competitiveness.

The motivation behind research into AI in manufacturing is multi-folded. It is driven by the imperative to enhance operational efficiency, optimize resource utilization, and ensure compliance with regulatory frameworks and ethical guidelines. Furthermore, the principles of trustworthy AI, green AI, human-centric AI, and adaptive AI provide guidance for the responsible and sustainable deployment of AI technologies in the manufacturing sector. By embracing these principles, manufacturers can not only unlock new opportunities for innovation and competitiveness but also contribute to the creation of a more ethical, sustainable, and human-centred future for the industry.

4.2 Application of AI

The application of AI in manufacturing covers a wide set of functionalities, substituting traditional processes or enhancing them with new tools and opening new topics for research. One prominent area of application is predictive maintenance, where AI algorithms analyse equipment data to forecast potential failures, thus enabling maintenance interventions and minimizing downtime (Tavola et al., 2020). Additionally, AI-powered robotic systems are increasingly employed in assembly lines for tasks ranging from product assembly to quality inspection, leading to improved precision and throughput.

Furthermore, AI-driven optimization algorithms are reshaping production planning and scheduling processes, enabling manufacturers to achieve greater resource utilization and cost efficiency, as well as to be able to satisfy more production orders and to minimize losses due to missed delivery deadlines. Moreover, AI-enabled supply chain management systems facilitate real-time monitoring and decision-making, enhancing responsiveness and resilience in the face of dynamic market conditions (Baryannis et al., 2019).

In line with the EC's guidelines, manufacturers are leveraging AI technologies to ensure compliance with regulations related to safety, environmental sustainability, and ethical considerations. Initiatives such as the European AI Alliance promote responsible AI adoption by advocating transparency, accountability, and fairness in AI-driven manufacturing systems.

4.3 AI challenges

Despite the transformative potential of AI in manufacturing, several challenges persist. Chief among these challenges is the integration of AI technologies into existing infrastructures and workflows, which often requires substantial investments in infrastructure, training, and change management. Moreover, ensuring data privacy and security remains a critical concern, particularly in light of the GDPR enforced by the EU, which protects the human actors from reification (or from becoming what Heidegger named *Bestand* in his “Die Frage nach der Technik”).

Another challenge is the ethical and societal implications of AI adoption, including issues related to job displacement, algorithmic biases (e.g., catastrophic events connected to lifelong learning), and the ethical use of data. Addressing these challenges implies a multidisciplinary approach that considers not only technological advancements but also their broader impacts on social sustainability.

A third aspect, strictly connected with the digitalization aspect, lies in the complex integration of AI technologies into existing manufacturing infrastructures and workflows. The heterogeneous nature of manufacturing systems often entails interoperability issues, requiring comprehensive strategies for data integration, system compatibility, and cross-platform communication. Moreover, ensuring the scalability and robustness of AI solutions across diverse manufacturing environments represents a technical issue, implying the development of adaptable and modular AI frameworks.

Furthermore, the dynamic and evolving nature of manufacturing processes poses challenges for AI systems, necessitating continuous adaptation and learning. AI algorithms must possess the flexibility and agility to respond to changing production demands, environmental conditions, and regulatory requirements in real-time, necessitating the development of adaptive and self-learning AI models capable of autonomous decision-making and optimization.

4.4 Use Cases Identification

The UC identification was made via a series of online meetings sessions organized between the industrial and academic partners of the Manufacturing Vertical of ENFIELD, which aimed at conducting a first assessment of the project and the industry's goals.

The outcome was a list of the first UCs for ENFIELD (summarized in TABLE 5) that is being exploited to foster the discussion with WP2 (the mapping between the use cases and the WP2 Pillars is presented in TABLE 6), conduct research internally in WP3, and the definition of the TES and TIS Open Calls in WP5. Important criteria to select these use cases were: i) relevance of the AI challenges for the WP2 Pillars, ii) data and/or infrastructure availability for AI testing and validation, iii) industrial partners strategic interest, and iv) potential to impact sustainable development goals, such as integration of RES and affordable energy.

Use case title	Where will be addressed?	Available data	Available infrastructure	Partners
UC1. Automatic identification of batch production patterns.	TES, TIS	Data retrieved from Testing and Experimental Facility	Testing and Experimental Facility for testing and further data generation	PREDICT
UC2. Smart Factory: Optimization of energy consumption in industrial robots.	Internal, TES, TIS	Data retrieved from Testing and Experimental Facility	Testing and Experimental Facility for testing and further data generation	PREDICT
UC3. Smart Factory: Toward more sustainable manufacturing industry.	TES, TIS	Not strictly required, but real and synthetic data available, gained in previous research experimentation about human involvement in manual assembly tasks	Testing and Experimental Facility for testing and further data generation	PREDICT
UC4. Flexible remanufacturing facility Optimization of remanufacturing process configuration, scalability, and efficiency.	Internal, TES, TIS	Data retrieved from Testing and Experimental Facility in previous projects about circular manufacturing	Testing and Experimental Facility for testing and further data generation, CIROS simulation environment for further data generation	DTI
UC5. Self-X Integration in manufacturing domain.	Internal, TES	Dataset related to previous experiments in predictive maintenance	Testing and Experimental Facility for testing and further data generation	POLIMI
UC6. Low-volume training dataset for computer vision.	Internal, TES, TIS	Image dataset of labelled circuital components images. Private datasets of defected machined parts.	Testing and Experimental Facility for testing and further data generation	POLIMI

TABLE 5 – MANUFACTURING VERTICAL USE CASES SUMMARY.

WP2 Pillar	Challenges	Keywords	Space vertical use cases
Green AI	Advancing Green AI on the Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Quantization and Pruning; Hardware Aware Architecture Search; On-Device Learning; Continual Learning (CL)	UC: 1, 2
	Optimizing Green AI in the Edge-to-Cloud Continuum	Distributed AI; Edge-to-Cloud Orchestration; Lifecycle Assessment (LCA); Hybrid AI Models; Continual Learning Adaptation.	UC:1, 2, 3
	Green AI Metrics Initiative	Standardization of Green-AI Metrics; Energy-Efficient Architectures; Lifecycle Environmental Impact; Computational Efficiency; Cross-Disciplinary Collaboration.	UC: 1, 2, 3, 6
Adaptive AI	Approaches to Incremental Learning Robustness and Trustworthiness	Incremental learning; Evolving systems; Concept drifts; Change adaptation; Robustness and Trust	UC: 2, 3, 5, 6
	Advancing Adaptive AI on The Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Continual Learning (CL); On-Device Learning; Hardware-aware AI compression; Adaptive Deep Reinforcement Learning.	UC: 1, 2, 3, 4, 6

WP2 Pillar	Challenges	Keywords	Space vertical use cases
	Neuroscience-Inspired Adaptive AI	Continual Learning, Lifelong Learning, Brain-Inspired AI, Multimodal Learning, Sparsity	UC: 1, 3, 4, 5
Human-centric AI	Evolving Symbolic Models for Decision-Making	Symbolic AI; Reinforcement learning; Learning; Data-driven; Evolving.	
	Novel Explainable AI Methods for Decision-Making	Explainability; Spatio-temporal Models; Decision making; Healthcare	UC: 3
	Interpretable Data-Driven Decision Support Systems	Interpretable decision making; Automatic decisions; Collaborative human decisions; Integrated collaborated environment; Medical domain	UC: 3
Trustworthy AI	Modeling Trust in Distributed AI System Architectures	Trustworthy AI; Distributed Systems; Trust Modelling; Software Architecture; Method Engineering	UC: 4, 5
	Detection of AI-Generated Content	AI content; Generative AI; LLM; Trust; Big data	
	Secure Voice Biometrics with Fake Voice Detection	Voice spoofing; Biometric security; Speech signal processing; Robust authentication; Acoustic analysis	

TABLE 6 - MAPPING BETWEEN MANUFACTURING VERTICAL AND THE WP2 PILLARS

Use case 1_Manufacturing. Automatic identification of batch production patterns.
Partners: PREDICT
Description: In the manufacturing industry, the implementation of condition-based maintenance practices for tool machines has revolutionized the approach to equipment upkeep (Tavola et al., 2020). This methodology involves gathering and analysing extensive data to gain insights into wear and failure patterns, thereby enhancing operational efficiency and ensuring plant safety. One crucial aspect of this approach is the labelling of time series data. After the data is collected and pre-processed, it undergoes labelling to identify various batch production patterns. These patterns serve as indicators of the "health condition" of the equipment. By discerning these patterns, manufacturers can optimize maintenance processes, pre-emptively addressing potential issues before they escalate into costly breakdowns. Labelling time series data enables manufacturers to understand the evolving condition of their equipment, facilitating proactive maintenance strategies. This understanding is particularly critical given the spatial and temporal distortions inherent in manufacturing environments. Additionally, the labelling process is compounded by the fact that only a limited number of patterns are labelled, necessitating precise identification and classification of these patterns for effective maintenance optimization (Jardine et al., 2016). **Industry challenge:** Despite the benefits of condition-based maintenance practices, several challenges exist in the labelling of time series data for tool machines. In this UC, the most significant one is the complexity of spatial and temporal distortions within manufacturing environments. These distortions can obscure the identification of relevant patterns, requiring sophisticated algorithms and techniques for accurate labelling. Moreover, the scarcity of labelled patterns poses a further challenge in reaching this target. With only a few patterns labelled, there's a heightened need for robust labelling methodologies that can generalize across various operational scenarios. This scarcity also underscores the importance of data quality and the necessity of strategies to augment labelled datasets through techniques such as semi-supervised learning or active learning. Furthermore, the dynamic nature of manufacturing operations necessitates near-real-time labelling capabilities. Timeliness is crucial for effective decision-making regarding maintenance interventions. Therefore, the development of efficient and scalable labelling frameworks capable of handling streaming data is imperative. Addressing these industrial challenges requires interdisciplinary collaboration between data scientists, domain experts, and manufacturing engineers. It entails the integration of advanced machine learning techniques with domain-specific knowledge to devise robust labelling strategies tailored to the unique requirements of tool machine maintenance in manufacturing settings.

State-of-the-art: In the realm of condition-based maintenance for tool machines, there's a significant evolution in control methods and data analysis to enhance operational efficiency and plant safety. Expert systems and DTW (Dynamic Time Warping) algorithms play crucial roles in predictive maintenance and performance monitoring. Expert systems, utilizing rule-based or closed-form control methods, are established methodologies for knowledge management and decision-making in complex industrial contexts. They interpret operational data to diagnose equipment status, offering recommendations to optimize maintenance operations and prevent unexpected failures. DTW algorithms are widely used for aligning and comparing unaligned time series data. Particularly useful in predictive maintenance, they enable comparison of current machine performance with historical models, even in the presence of temporal variations and non-uniform speeds. This flexibility is essential for detecting anomalies and dynamically adapting maintenance strategies to actual equipment conditions. Despite advancements, challenges persist. The complexity of modern production systems and the vastness of generated data necessitate more sophisticated approaches for integration and analysis. Accurately interpreting operational data and translating insights into effective actions require a deeper understanding of industrial context and production dynamics. Addressing these challenges demands interdisciplinary collaboration among engineers, data scientists, and domain experts. Integrating expert systems with advanced machine learning techniques and DTW algorithms could enable more effective monitoring and predictive maintenance of tool machines, ultimately enhancing reliability and productivity in industrial facilities. **Expected impacts and outcomes:** A Green AI algorithm embedded to perform all or part of the processing on the edge minimizing hardware power consumption, IoT protocol efficiency, communication overhead, data storage energy usage. An AI-based solution to improve the characterization of the phase's labels and better efficiency of the recognition process. **AI requirements:** 1) Green AI for edge to cloud continuum and AI systems embedded in our products. AI based methods to improve data sample efficiency, number of learning parameters through effective regularization schemes. 2) Adaptative IA on the edge exploiting historical data to perform pattern recognition (e.g., reinforcement learning, brain-inspired algorithms in continual learning, learning under noisy labels, automated transfer training) to address the problem of very few or no labelled data.

Use case 2_Manufacturing. Smart Factory: Optimization of energy consumption in industrial robots.
Partners: PREDICT
Description: The optimization of energy consumption in industrial robots is paramount for enhancing operational efficiency and sustainability within smart factory environments. By minimizing energy usage, manufacturers can reduce operating costs, improve performance, and prolong the lifespan of robotic systems during part manufacturing processes. In this use case, industrial robots play a pivotal role in automating various tasks across different industries, including automotive, electronics, and aerospace. These robots perform a myriad of functions, such as assembly, welding, painting, and material handling, requiring substantial energy inputs. Therefore, optimizing energy consumption in industrial robots is crucial for maximizing resource utilization and minimizing environmental impact. Several strategies can be employed to achieve energy optimization in industrial robots. These include implementing advanced motion planning algorithms to minimize unnecessary movements and idle times, optimizing trajectory planning to reduce energy-intensive accelerations and

decelerations, and deploying predictive maintenance techniques to identify and address energy inefficiencies proactively.
Furthermore, the integration of sensors and IoT (Internet of Things) technologies enables real-time monitoring of energy usage and environmental conditions, allowing for dynamic adjustments to optimize energy consumption based on production requirements and external factors such as ambient temperature and humidity.

Industry challenge: Despite the potential benefits, optimizing energy consumption in industrial robots presents several challenges: one of them is the dynamic nature of manufacturing processes, which can lead to variability in energy demands and operational conditions. Balancing energy optimization with production efficiency and quality requirements requires advanced control strategies capable of adapting to changing production scenarios in real-time.

Moreover, the complexity of industrial robot systems, characterized by multiple degrees of freedom and interconnected subsystems, raises challenges for accurate energy modelling and prediction. Developing precise models that capture the energy consumption dynamics of robotic actuators, motors, and controllers under different operating conditions is essential for effective energy optimization.

Additionally, the scalability of energy optimization solutions across different types of industrial robots and manufacturing environments introduces another industrial challenge: while certain optimization techniques may be effective for specific robot models or applications, generalizing these approaches to diverse robotic systems and production settings requires robust methodologies and adaptable algorithms.

Furthermore, ensuring interoperability and compatibility with existing automation systems and control architectures is essential for seamless integration of energy optimization solutions into smart factory environments. Overcoming these challenges necessitates collaborative efforts among manufacturers, technology providers, and research institutions to develop innovative approaches and standards for energy-efficient robotics in industrial settings.

Addressing these challenges will not only drive improvements in energy efficiency and sustainability but also foster innovation and competitiveness in the era of smart manufacturing.

State-of-the-art: AI has modified various tools of industrial robotics, ranging from proper robot selection to programming working schedules, through conducting regular maintenance.

For what concerns the robot selection, AI-driven algorithms leverage on ML techniques to analyse vast datasets comprising factors such as payload requirements, workspace constraints, and task complexity. By considering these parameters, AI systems can recommend the most suitable robot models for specific manufacturing applications, optimizing performance and resource utilization. Furthermore, AI-powered simulation platforms enable virtual testing and validation of robot configurations, streamlining the selection process and reducing implementation risks.

For what concerns the programming of working schedules, AI-based scheduling algorithms often use predictive analytics and optimization techniques to generate efficient working schedules for robotic systems. These algorithms rely on production targets, resource availability, and workflow dependencies to dynamically allocate tasks and minimize idle time. Additionally, AI-enabled adaptive scheduling systems can respond to real-time changes in demand or production conditions, ensuring optimal resource utilization and timely completion of manufacturing tasks.

For what concerns regular maintenance, AI is a well-known approach in the domain of predictive maintenance strategies. By analysing sensor data and historical performance metrics, ML algorithms can detect early signs of component degradation or failure, enabling proactive maintenance interventions. These solutions are usually implemented through techniques such as rNN and SVM, to forecast maintenance requirements based on patterns in sensor data. This approach minimizes downtime, reduces maintenance costs, and extends the operational lifespan of robotic systems.

Expected impacts and outcomes: The overall UC achievements are supposed to improve the efficiency of the factory energy management system by providing tools to transform current

manufacturing processes into more efficient and environmentally friendly productions, by building new solutions to increase sustainability of industrial robot operations in terms of productivity enhancement of part manufacturing and by increasing the lifespan of the robot during part manufacturing. Evidence gained during the testing phases are welcome to contribute to the scientific body of knowledge via the submission of one or more peer-reviewed article. **AI requirements:** 1) Green AI to optimize the energy use of the manufacturing process (e.g., to select the least consuming or polluting assets, to optimize the number of assets in operation, to limit engine fouling and start-up emissions). 2) Adaptive AI for efficient programming of working schedule regarding the workload plan by learning from previous experiences.

Use case 3_Manufacturing. Smart Factory: Toward more sustainable manufacturing industry.
Partners: PREDICT
Description: The concept of the so-called "Industry 5.0" represents a paradigm shift towards a more holistic and sustainable approach to manufacturing, where digital transformation converges with environmental stewardship. While the manufacturing industry has taken strides in digitalization through the previous so-called "Industry 4.0" initiative, the integration of sustainability considerations into manufacturing processes remained underdeveloped, despite the interest from the academic and practitioners' communities. In this UC, the focus is on leveraging advanced digital technologies to optimize manufacturing operations while minimizing environmental impact across the entire product lifecycle. Rather than solely emphasizing productivity gains, the objective is to achieve a balance between economic prosperity, social responsibility, and environmental sustainability. Key components of this use case include: 1. Comprehensive data collection: building upon the foundation of "Industry 4.0", manufacturing plants collect and integrate data from various sources, including IoT sensors, production equipment, and supply chain systems. This comprehensive data collection enables a detailed understanding of manufacturing processes and their environmental footprint. 2. Integrated Sustainability Metrics: Beyond traditional productivity metrics, the use case incorporates sustainability indicators into the monitoring and optimization framework. This includes tracking resource consumption (e.g., energy, water, raw materials), greenhouse gas emissions, waste generation, and other environmental impacts throughout the product lifecycle. 3. Lifecycle Assessment: Employing life cycle assessment (LCA) methodologies, the use case evaluates the environmental footprint of products from raw material extraction to end-of-life disposal or recycling. By conducting LCA analyses, manufacturers can identify opportunities for resource efficiency improvements, waste reduction, and emissions mitigation at each stage of the product lifecycle. 4. Closed-Loop Systems: Implementing closed-loop systems and circular economy principles, the use case aims to minimize waste generation and maximize resource utilization. This involves designing products for disassembly, remanufacturing, and recycling, as well as establishing reverse logistics networks to facilitate the return and recovery of end-of-life products and materials. **Industry challenge:** Despite the potential benefits of integrating sustainability into manufacturing operations, several challenges must be addressed to realize the vision of "Industry 5.0": 1. Data integration and interoperability: integrating different data sources and systems arises technical challenges, in particular with respect to data standardization, compatibility, and interoperability. Designers must overcome these barriers to data sharing and collaboration to enable comprehensive lifecycle assessments and sustainability analyses.

2. Complexity of sustainability metrics: developing robust sustainability metrics and assessment methodologies that capture the multidimensional nature of environmental impacts is a complex endeavour. Manufacturers face issues in quantifying and benchmarking sustainability performance across diverse product portfolios and manufacturing processes.
3. Supply chain transparency: achieving sustainability goals requires transparency and collaboration throughout the supply chain. However, ensuring supply chain transparency and traceability, especially for raw material sourcing and supplier practices, presents logistical and governance challenges.
4. Cost and investment considerations: implementing sustainable manufacturing practices often requires investments in technology, infrastructure, and workforce training. Manufacturers are supposed to balance the costs and benefits of sustainability initiatives while navigating competitive market dynamics and financial constraints.

Addressing these challenges requires a concerted effort from stakeholders across the manufacturing ecosystem, including manufacturers, technology providers, policymakers, and civil society organizations. By embracing the principles of Industry 5.0 and fostering innovation in sustainable manufacturing practices, the industry can pave the way towards a more resilient, equitable, and environmentally responsible future.

State-of-the-art: in this context, AI plays a crucial role in advancing sustainability objectives across various facets of manufacturing operations.

For example, one of the most debated strategies imply a Zero-Defect Manufacturing (ZDM) approach, which, when AI-driven, leverages on ML algorithms to detect and prevent defects in real-time (e.g., analysing production data and sensor readings, patterns indicative of potential defects are identified, and corrective actions are triggered to maintain product quality and minimize waste). Furthermore, AI-powered anomaly detection algorithms facilitate early fault detection and root cause analysis, enabling manufacturers to implement proactive measures and continuously improve process reliability.

Alternatively (or in addition to this), waste reduction and recycling techniques can rely on AI optimization algorithms to optimize resource utilization and minimize waste. By analysing production data and environmental factors, these algorithms optimize material flows, production schedules, and energy usage to reduce waste and environmental impact. Additionally, AI-powered sorting and recycling systems enhance the efficiency and effectiveness of waste segregation and recovery processes, enabling manufacturers to extract value from discarded materials and promote circular economy principles within the smart factory environment.

Lastly, a pervasive technology involving AI-enabled sensing tools can enable near-real-time monitoring of process parameters and product quality. Integrated with production equipment and inspection systems, AI algorithms can analyse sensor data to detect deviations from desired quality standards and trigger corrective actions. This near-real-time monitoring improves product quality while minimising wastes and rework, aligning with sustainability objectives by reducing the environmental footprint of manufacturing operations. Furthermore, AI-powered image recognition and machine vision systems automate inspection tasks, increasing promptness and accuracy of product quality, further enhancing the efficiency and sustainability of manufacturing processes within the smart factory framework.

Expected impacts and outcomes: The overall UC achievements are supposed to optimize sustainable production, considering the multi-objective approach of having a minimal ecological impact, while ensuring ZDM. ML algorithms powered by large, labelled data related to product quality provided by Non-Destructive Inspection systems for zero defect optimization are supposed to be investigated and eventually deployed in a small-scale application.

AI requirements: 1) Green AI approach for zero-defect manufacturing (e.g., optimization techniques and meta-heuristics algorithms)

2) Adaptative AI (e.g., dataset distillation, experience replay) to address several scenarios given a machine or a production-line using novel approaches to remember experiences in a lifetime without storing a large amount of data. Sharing experiences should also enable knowledge transfer from one task to another, leading to fast convergence and better performance. 3)A Human-centric IA based algorithm that integrates human expertise and decision making into machine learning and AI systems. This could be achieved by allowing human intervention in some of the decision cycle of the system and enabling more accurate and efficient models that can adapt to changing environments and data inputs.

Use case 4_Manufacturing. Flexible remanufacturing facility: optimization of remanufacturing process configuration, scalability, and efficiency.
Partners: DTI
Description: Given the global concern over waste streams and resource scarcity, companies are increasingly turning to remanufacturing as a more sustainable and "circular" solution. Remanufacturing involves reclaiming used products, recycling components, refurbishing where necessary, and occasionally remanufacturing them to extend their lifecycle. Key processes in remanufacturing include sorting, grading, separation, and cleaning operations, each presenting unique challenges due to the variability and unknown volume of incoming used products. To address these challenges, a remanufacturing facility must be flexible, scalable, and adaptable to accommodate varying input materials and changing product requirements. The facility must optimize its operations to maximize efficiency and resource utilization while maintaining product quality and compliance with regulatory standards. This UC aims at leveraging on AI approaches to enhance the flexibility, scalability, and efficiency of remanufacturing processes, enabling manufacturers to match sustainability KPIs, as well as to address supply chain constraints effectively. **Industry challenge:** despite the potential benefits of remanufacturing, several challenges are supposed to be overcome to materialise its potential: 1. Variability and uncertainty in input materials: the variability and unknown volume of incoming used products pose challenges in process planning and resource allocation. Remanufacturing facilities must develop adaptive strategies to accommodate fluctuations in input materials while maintaining process efficiency and product quality. 2. Complexity of process configuration: remanufacturing processes encompass a range of operations, including sorting, grading, refurbishing, and remanufacturing. Optimising process configuration and sequencing to maximize resource utilization and minimize waste requires sophisticated planning and scheduling algorithms. 3. Scalability and adaptability: as demand for remanufactured products grows, facilities must scale their operations to meet increasing production volumes while remaining agile and adaptable to changing market dynamics and product specifications. 4. Quality assurance and compliance: ensuring product quality and compliance with regulatory standards is paramount in remanufacturing. Implementing robust quality inspection and defect detection systems is essential to identify and rectify issues early in the process. Addressing these challenges requires innovative approaches and technologies, including AI-driven solutions that leverage on ML, data analytics, and automation to optimise process configuration, enhance scalability, and improve efficiency in remanufacturing operations. **State-of-the-art:** In the remanufacturing domain, AI is improving various aspects of the process. As a matter of example, for what concerns quality inspection, defect detection, and object recognition, AI-powered vision systems enable automated quality inspection and defect detection in remanufactured products: ML algorithms analyse images to identify defects, classify

components, and recognise objects, ensuring product quality and compliance with quality standards. In the domain of automation/robot behaviour adaptation and learning, AI algorithms enable robots to adapt their behaviour and learn from experience in remanufacturing tasks. Reinforcement learning techniques allow robots to optimize their actions based on feedback from the environment, improving efficiency and adaptability in complex assembly and disassembly processes. With respect to process monitoring and simulation, AI-driven monitoring and simulation tools provide near-real-time insights into remanufacturing processes. These tools analyse live data streams from sensors and production systems, visualizing heterogeneous data to identify inefficiencies, optimize workflows, and simulate scenarios for process improvement. **Expected impacts and outcomes:** The UC is supposed to benefit of the contribution derived by new tools in the context of adaptive quality inspection, defect detection, and object recognition algorithms, able to consider in a quick and intuitive way new products and new defects. A further or alternative contribution to this Use Case could consist in the design/development of a decision-making tool to optimise the monitoring of remanufacturing processes. **AI requirements:** 1) Adaptive AI to adapt to new products and defects, to define new designs and configurations of remanufacturing lines, and to support decision-making tools to monitor these lines. 2) Trustworthy AI to ensure that new design and new products are properly efficient, and cybersecurity.

Use case 5_Manufacturing. Self-X Integration in manufacturing domain.
Partners: POLIMI
Description: The integration of Self-X technologies, encompassing self-configuring, self-healing, self-optimising, and self-protecting capabilities, within the manufacturing domain represents a transformative paradigm shift. This integration aims to imbue manufacturing systems with autonomy and adaptability, enabling them to autonomously optimize performance, configure parameters based on contextual changes, diagnose faults, and even rectify issues without human intervention. Within this use case, Self-X integration finds application in various manufacturing processes, including assembly lines, machining operations, and logistics management. For instance, self-optimization algorithms can dynamically adjust production parameters such as speed, temperature, and pressure to maximize efficiency and minimize energy consumption. Self-configuration capabilities enable manufacturing systems to adapt to changes in product specifications or production requirements seamlessly. Self-diagnosis mechanisms continuously monitor equipment health and identify potential faults or deviations from optimal performance. Moreover, self-healing functionalities facilitate rapid response to identified issues, either through automated adjustments or by triggering maintenance alerts for human intervention when necessary. The implementation of Self-X integration promises to revolutionize manufacturing operations by enhancing agility, resilience, and efficiency across the production lifecycle. By leveraging advanced sensing technologies, real-time data analytics, and machine learning algorithms, manufacturing systems can evolve from passive tools to intelligent entities capable of self-management and continuous improvement. **Industry challenge:** Despite the potential benefits, the integration of Self-X technologies in the manufacturing domain poses several significant challenges. One of the primary challenges is ensuring compatibility and interoperability with existing legacy systems and infrastructure. Many manufacturing facilities operate with heterogeneous equipment and control systems, necessitating seamless integration of Self-X capabilities without disrupting ongoing operations.

Moreover, the complexity of manufacturing processes and environments introduces challenges related to system reliability and robustness. Self-X algorithms must exhibit high levels of accuracy and resilience to diverse operating conditions, environmental factors, and potential disturbances. Additionally, ensuring data security and privacy is a strong burden in today's society, particularly as manufacturing systems become increasingly interconnected and rely on data exchange for autonomous decision-making. Furthermore, the human-machine interaction aspect warrants attention: while Self-X technologies aim to minimize human intervention, effective collaboration between automated systems and human operators is essential. Designing intuitive interfaces and decision-support systems that facilitate transparent communication and shared decision-making between humans and machines is critical for successful implementation. Addressing these industrial challenges requires a holistic approach, encompassing technological innovation, organizational readiness, and regulatory considerations. Collaborative efforts among technology providers, manufacturers, and regulatory bodies are essential to overcome barriers and realize the full potential of Self-X integration in the manufacturing domain. **State-of-the-art:** One of the most experienced solutions to these issues is the iteration of the training phases of algorithms, but this mitigation presents either high resource consumption or can lead to catastrophic interferences, which constitute a severe risk for the performances and for addressing responsibilities. In recent years, the practitioners' community resumed however frameworks and requirements from the Control domain (namely MAPE-K and Self-X) in order to grant the controlled systems the capability to self-adapt to unpredictable events. **Expected impacts and outcomes:** Starting from a defined and centralised software architecture, the proposed solution is supposed to be able to be AI pipelines able to deal and implement self-X capabilities. The solution is supposed to be tailored onto a lab-scale production environment and to deal with non-PLC signals (e.g., energy consumption) clustering the production in new defined classes. Alternatively, real-like industrial datasets are also available. A publication related to the state of the art and the contribution of this small-scale application is supposed to be the ideal mean to report the carried on activities and the achieved successes. **AI requirements:** Adaptive AI to adapt to new products and recipes. Trustworthy AI to ensure that new design and new products are properly and efficiently produced.

Use case 6_Manufacturing. Low-volume training dataset for computer vision.
Partners: POLIMI
Description: In contemporary manufacturing, quality control operations are increasingly reliant on Computer Vision (CV) technology. This technology employs Neural Networks (NN) to detect and localize defects in products, enabling automated decision-making systems to determine whether to discard defective items or initiate rework processes (based on defect type and severity). Within this context, the availability of high-quality training datasets is crucial for the development and optimization of computer vision models. However, in low-volume manufacturing scenarios (e.g., OEM, aerospace industry), obtaining sufficient labelled data for training can be challenging. This shortage of data may hinder the effectiveness and generalization capability of computer vision systems, impacting their accuracy in defect detection and localization tasks. To address this challenge, manufacturers must devise strategies for creating and augmenting low-volume training datasets for computer vision applications. These strategies may involve data synthesis techniques, transfer learning from related domains, or leveraging semi-supervised learning approaches to maximize the utility of available data while minimizing the need for extensive manual labelling.

Industry challenge: The utilization of CV for quality control introduces several challenges, particularly concerning the availability and quality of training datasets. In low-volume manufacturing environments or for niche product lines, collecting enough labelled data for training robust NN models can be indeed problematic. This lack of data may lead to overfitting or limited generalization performance, undermining the reliability of defect detection systems.

Moreover, ensuring the representativeness and diversity of training data is essential for developing robust and reliable computer vision models. Biases or inadequacies in the training dataset may result in the model's inability to accurately detect defects across various product variations or production conditions, potentially leading to false positives or false negatives in quality control operations.

Furthermore, maintaining the relevance and currency of training datasets poses ongoing challenges. As manufacturing processes evolve or new defect types emerge, the training data must be regularly updated and augmented to reflect these changes accurately. This necessitates continuous data collection, annotation, and refinement efforts to ensure the effectiveness and adaptability of computer vision systems over time.

Addressing these challenges requires collaborative efforts between manufacturing engineers, data scientists, and domain experts. Developing robust methodologies for generating and curating low-volume training datasets, alongside advancements in data augmentation techniques and transfer learning approaches, is essential for enhancing the reliability and scalability of computer vision-based quality control systems in low-volume manufacturing environments.

State-of-the-art: One notable advancement in this field is the widespread adoption of Convolutional Neural Networks (CNNs), particularly the YOLO (You Only Look Once) algorithms. YOLO algorithms, characterized by their real-time object detection capabilities, have revolutionized defect identification and localization tasks in manufacturing settings. Unlike traditional detection methods that rely on sliding window approaches, YOLO algorithms enable simultaneous detection and classification of defects within a single pass through the neural network, significantly reducing computational overhead and enabling real-time inspection on production lines.

Beyond YOLO, advancements in deep learning architectures, such as Faster R-CNN and SSD (Single Shot MultiBox Detector), have further enhanced the accuracy and speed of defect detection systems. These architectures leverage feature extraction networks like ResNet and MobileNet to capture intricate patterns and textures indicative of defects, enabling robust performance across diverse product types and manufacturing conditions.

Moreover, the integration of transfer learning techniques has facilitated the development of defect detection models with limited training data. By pre-training CNNs on large-scale image datasets like ImageNet, researchers can transfer learned features to domain-specific defect detection tasks, mitigating the challenges associated with data scarcity in low-volume manufacturing environments.

Finally, the emergence of explainable AI methodologies has addressed concerns regarding the interpretability and trustworthiness of computer vision-based quality control systems. Techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping) provide insights into the decision-making process of CNNs, enhancing transparency and facilitating human oversight in critical manufacturing processes.

In summary, the convergence of deep learning architectures, transfer learning strategies, and explainable AI techniques, coupled with the pioneering contributions of YOLO algorithms, has propelled computer vision-based quality control to new heights of accuracy, efficiency, and interpretability in contemporary manufacturing environments.

Expected impacts and outcomes: Development of an algorithm able to recognise defected parts and to classify the defects, starting from a limited size database (~1000 total samples). Samples available from demanufactured PCB components or from real manufactured mechanical

parts. A comparative analysis of different algorithms and methodologies used is also supposed to be delivered as a peer-reviewed publication. **AI requirements:** Green AI avoiding computational waste localised in the training. Adaptive AI to adapt to generical defects even never previously detected.

5 Space vertical

5.1 Context and motivation

In recent years, there has been a growing interest in space development, providing researchers with space-based EO capabilities. EO satellites are covering the Earth with multispectral, radar, and more recently hyperspectral images providing high quality data on weekly basis (e.g., from Sentinel-1, Sentinel-2, Landsat, DESIS, EnMAP) as well as on a daily basis (e.g., PlanetScope satellite). Other satellite sensors are covering the Earth twice day such as NASA's MODIS which derives essential environmental variables, including evapotranspiration, land surface temperature, and vegetation indices.

In 2015, United Nations set 17 world Sustainable Development Goals (SDG) with the aim to bring "peace and prosperity for people and the planet, now and into the future". Remote sensing with the capabilities of environmental monitoring and securing society's resilience in combination with AI can contribute to reach SDG goals. This is because space-based remote sensing offers enormous amounts of open access satellite data that can be used by AI models, advancing in this way the research and industrial development in space applications. Several sectors, including agriculture, maritime, natural disaster risk reduction, atmosphere and climate change mitigation have used AI for prediction, prevention, monitoring and detecting tasks (Dupont et al., 2020; Hunt et al., 2019; Le Cozannet et al., 2020). In addition, AI is widely used for the optimization of satellite and aerospace operations (Fourati & Alouini, 2021).

The combination of EO and AI can contribute to the monitoring of our planet on the following:

- Monitoring of Earth's surface activities in large scale and even in near-real-time (satellites are capturing data in daily or weekly basis. Geostationary satellites are further enhancing near-real-time monitoring).
- Early warning systems for different applications such as natural disasters, disease monitoring, human health, illegal activities.
- Reduce the costs for different activities such as crop ground-truthing, disease monitoring, groundwater monitoring that demand many person-days.
- Identifying correlations between biophysical processes and satellite derived data.

5.2 Application of AI

Different tasks regarding the agricultural industry have been enhanced with the adaptation of machine learning methodologies trained with satellite data such as crop classification, yield prediction, crop water stress, disease monitoring and other agricultural practices (e.g., fertilizations, irrigation, tilling etc.) (Karthikeyan et al., 2020; Martos et al., 2021; Sishodia et al., 2020). For example, accurate crop classification improves food security monitoring, empowers market analysis, and optimizes agricultural compensations from EU fundings. AI algorithms enables researchers to develop models trained with satellite data that can classify crops with an accuracy over 90%.

Satellite missions such as Calypso, GEO, METEOSAT, AEOLUS and Sentinel-3 are providing data to monitor the atmosphere by capturing aerosol profiles (Jiang et al., 2021; Zhang et al., 2020). These data can also be fused with in-situ data obtained from LiDAR campaigns. In fact, out planet suffers from natural disasters like earthquakes, landslides, floods, and extreme weather events caused by the climate change which can be monitored using satellite data. For example, EO in combination with AI models can assist in monitoring wildfires, optimize the mapping of flooded areas and assess different stages of floods, prior, during and after the occurrence of the event(Kemper & Kemper, 2020; Munawar et al., 2022; Tan et al., 2021).

The maritime sector is threatened by illegal activities in the sea such as fishing near to coral reefs, immigration of people, pollution from oil spills and illegal shipping. Remote sensing and EO imagery can help to track those illegal activities and monitor pollution incidents. AI object-detection models are widely used. Those algorithms can precisely detect ships and thus identify illegal activities such as shipping or immigration.

5.3 AI challenges

Earth Sciences like agriculture, water resources management, monitoring of natural disasters and others require domain knowledge. On the other hand, applications like the detection of people immigration and illegal fishing require trustworthiness. Combining Earth Sciences with AI leads to a lot of threats and challenges regarding integration with existing systems, reusability, replicability, and ethics. Thus, there are a lot of opportunities on provenance of AI, explainability and interpretability(Sun et al., 2022). Furthermore, because more of the applications are affected by the variability of climate and they are changing over the years, there is also an urgent need to address those issues. Satellite on-board processing for the generation of Analysis Ready Data (ARD) utilizes huge amounts of power and this is also in concern of the community(Guerrisi et al., 2023; Ortiz et al., 2023).

Therefore, ENFIELD's pillars can contribute to overcome those challenges:

- **Human-centric AI** can enhance the interpretability and explainability of the AI models in space applications for earth sciences.
- **Green AI** can contribute to developing low power consumption algorithms for on-board processing in order to develop cloud-free products, analysis ready products or even compressing images.
- **Adaptive AI** is useful for the continuous training of EO applications in order to adapt for the new status of the planet.
- **Trustworthy AI** can help by creating more robust EO applications to avoid adversarial attacks and be resistant in errors.

5.4 Use Cases Identification

The UC identification was made via a series of online meetings sessions organized between the industrial and academic partners of the Space Vertical of ENFIELD, which aimed at conducting a first assessment of the project and the industry's goals.

The outcome was a list of the first UCs for ENFIELD (summarized in TABLE 7) that is being exploited to foster the discussion with WP2 (the mapping between the use cases and the WP2 Pillars is presented in TABLE 8), conduct research internally in WP3, and the definition of the TES and TIS Open Calls in WP5. Important criteria to select these use cases were: i) relevance of the AI challenges for the WP2 Pillars, ii) data and/or infrastructure availability for AI testing and validation, iii) industrial partners strategic interest, and iv) potential to impact sustainable development goals, such as integration of RES and affordable energy.

Use case title	Where will be addressed?	Available data	Available infrastructure	Partners
UC1. AI satellite on-board processing model for cloud and cloud shadow masking on hyperspectral images with a metadata perspective	TES, TIS	Yes	Not required	ECoE
UC2. Causal Machine Learning model to identify agricultural practices aiding in yield productivity improvement using EO data.	TES, TIS	Satellite images (from Sentinel 2)	Not required	ECoE
UC3. Loss of satellite communication	Internal, TES, TIS	Not required	Not required	BAS
UC4. Icing condition prediction	TES, TIS	Satellite images (from Sentinel 1 and Sentinel 2), weather reports	Not required	BAS
UC5. Flood zone mapping	TES, TIS	Satellite images (from Sentinel 1 and Sentinel 2), weather reports	Not required	NR
UC6. Fast and accurate atmospheric radiative transfer (RT) simulations for satellite microwave instruments	TES	OA datasets	Not required	CHAMLERS
UC7. Generative models for 3D cloud fields	TES	CloudSat and OA datasets	Not required	CHALMERS
UC8. Cost-effective precipitation retrievals	TES	Meteosat	Not required	CHALMERS
UC9. Foreign object debris (FOD) detection	Internal, TES, TIS	OA datasets	Not required	BAS
UC10. Automatic Speech Recognition (ASR) for automatic callsign detectio on ATC voice communications	TES, TIS	OA datasets	Not required	BAS
UC11. Monitoring of maritime illegal activities	TES, TIS	Satellite images (from Sentinel 1 and Sentinel 2)	Not required	ECoE
UC12. Forecasting soil water availability for monitoring illegal abstractions	TIS	Data from in-situ meteorological networks, Copernicus Atmosphere Monitoring Service (CAMS), Copernicus Climate Change Services (C3S), NASA's MODIS satellite spectroradiometer, NASA's GPM and EUMETSAT satellites	Not required	ECoE

TABLE 7 - SPACE VERTICAL USE CASES SUMMARY.

WP2 Pillar	Challenges	Keywords	Space vertical use cases
Green AI	Advancing Green AI on the Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Quantization and Pruning; Hardware Aware Architecture Search; On-Device Learning; Continual Learning (CL)	UC: 1, 8, 11, 12
	Optimizing Green AI in the Edge-to-Cloud Continuum	Distributed AI; Edge-to-Cloud Orchestration; Lifecycle Assessment (LCA); Hybrid AI Models; Continual Learning Adaptation.	UC: 1, 5, 8, 11, 12
	Green AI Metrics Initiative	Standardization of Green-AI Metrics; Energy-Efficient Architectures; Lifecycle Environmental Impact; Computational Efficiency; Cross-Disciplinary Collaboration.	UC: 1, 5, 8, 12
Adaptive AI	Approaches to Incremental Learning Robustness and Trustworthiness	Incremental learning; Evolving systems; Concept drifts; Change adaptation; Robustness and Trust	UC: 3, 4
	Advancing Adaptive AI on The Edge: Innovations for Sustainable, Efficient, and Continual Learning in Edge Computing	Continual Learning (CL); On-Device Learning; Hardware-aware AI compression; Adaptive Deep Reinforcement Learning.	UC: 3, 4
	Neuroscience-Inspired Adaptive AI	Continual Learning, Lifelong Learning, Brain-Inspired AI, Multimodal Learning, Sparsity	
Human-centric AI	Evolving Symbolic Models for Decision-Making	Symbolic AI; Reinforcement learning; Learning; Data-driven; Evolving.	
	Novel Explainable AI Methods for Decision-Making	Explainability; Spatio-temporal Models; Decision making; Healthcare	UC: 2, 3, 4, 6
	Interpretable Data-Driven Decision Support Systems	Interpretable decision making; Automatic decisions; Collaborative human decisions; Integrated collaborated environment; Medical domain	UC: 2, 3, 4, 6
Trustworthy AI	Modeling Trust in Distributed AI System Architectures	Trustworthy AI; Distributed Systems; Trust Modelling; Software Architecture; Method Engineering	UC: 7, 9
	Detection of AI-Generated Content	AI content; Generative AI; LLM; Trust; Big data	UC: 7, 9
	Secure Voice Biometrics with Fake Voice Detection	Voice spoofing; Biometric security; Speech signal processing; Robust authentication; Acoustic analysis	UC: 10

TABLE 8 - TABLE 4 - MAPPING BETWEEN SPACE VERTICAL AND THE WP2 PILLARS.

Use case 1_SPACE. AI satellite on-board processing model for cloud and cloud shadow masking on hyperspectral images with a metadata perspective.
Partners: ECoE
Description: Cloud masking and cloud shadow masking can be a difficult task on hyperspectral satellite images for entry-level users and researchers on the disciplines of Remote Sensing and EO in general. The main objective of Use case 1_SPACE is the delivery of Analysis Ready Data (ARD) hyperspectral data directly from the satellites by generating on-board cloud and cloud shadow masks accompanied by metadata for easier utilization in different applications. **Industry challenge:** Satellite on-board processing often requires high power consumption or lacks in terms of computational power for AI tasks. Optical sensors, since their dawn, are suffering from cloud coverage resulting in unusable raster images. Cloud masking and Cloud shadow masking is a procedure enhancing the provision of ARD to users. In addition, hyperspectral sensors are adding more complexity in detecting/classifying clouds and cloud shadows due to their high dimensionality regarding number of available bands (features). **State-of-the-art:** Currently, industry employs components-of-the-shelf (COTS) for on-board processing such as Vision Processing Units (VPUs), Field Programmable Gate Arrays (FPGAs) and Graphical Processing Unit (GPU)-based processing platforms. Each of those COTS offers different capabilities with different power consumption requirements. To ensure no loss of features, satellites are keeping raw image files in-memory, which results in greater needs in terms of computational power when processing.

Expected impacts and outcomes: Contributing with a feature selection model to reduce dimensionality for cloud and cloud shadow classification on hyperspectral images. By decreasing the dimensionality complexity by employing optimized feature selection methods, on-board processing will require less computational power and consequently less power consumption. Outcoming image datasets will be enhanced by metadata indicating cloud coverage upon geospatial landmarks (e.g., cities). **AI requirements:** 1) Identifying optimized feature selection methods for cloud masking problems to reduce dimensionality. 2) Pre-trained neural network model for direct deep learning (DL) inference. Suggested pillar: Green AI

Use case 2_SPACE. Causal Machine Learning model to identify agricultural practices aiding in yield productivity improvement using EO data.
Partners: ECoE
Description: The integration of AI and Remote Sensing has revolutionized the agricultural industry all over the world. Farmers can really benefit from novel Machine Learning applications. The objective of Use case 2_SPACE is the development of a Causal Machine Learning (CML) model to identify the effect of different agricultural practice on yield productivity. **Industry challenge:** Personalized applications dedicated to farmer's practices in combination with EO data are still an undiscovered path. Farmers must be in the centre to help them improve their yield productivity by identifying the cause effect of the different agricultural practices (e.g., irrigation management, fertilizations) to yield productivity. **State-of-the-art:** Industrial applications utilizing EO data for yield prediction and estimation in order to support farmers are arising. CML is still undiscovered withing the discipline of Earth Sciences. CML can help through its capabilities to explore a problem further than correlations of data to a problem by detecting the cause and estimating the cause's effect. Causal Inference and Causal Analysis by employing Double Machine Learning (DML) and other more traditional methodologies are widely used in the sectors of economics and business intelligence. **Expected impacts and outcomes:** Contributing with an end-to-end Causal Analysis and CML model to support agricultural industry and farmers. Identifying the impact of agricultural practices to yield productivity. **AI requirements:** Development of EO-based applications integrated with innovative technologies like Causal Analysis, Double Machine Learning and CML to identify causal effect of different agricultural practices in yield productivity and farming industry's increase in turnover. Suggested pillar: Human-centered AI

Use case 3_SPACE. Loss of satellite communication
Partners: BAS
Description: Loss of satellite communication prediction system for urban air mobility solution based on synthetic and in-flight captured data. **Industry challenge:** Continuous communication between autonomous aircraft and the control center is a key enabler for monitoring and supervising operations, especially to send and receive command and control data. For urban air mobility applications (i.e., air taxi), satellite-based communications are a potential technology to achieve ubiquitous and scalable operations through different regions. Robustness and availability of the communication links are important factors to understand the safety of the operations and the ability of predicting contingencies like loss of link beforehand (even in planning phases) is critical to minimize disruptions in high scale operations. **State-of-the-art:** Currently, availability and performance of communication systems is assessed by using traditional radio frequency propagation models (usually, statistical models extracted after experimental measurement campaigns). This approach has limitations in dynamic environments

where the number of users, weather conditions or physical environments, among others, can change over time affected to the propagation conditions. The proposed system aims to use both synthetic and during flight data (same flight path will be used several times a day) to train a model (likely using LSTM RNN or other time-affected method) a predictor for this type of situation. **Expected impacts and outcomes:** Incorporate tools that contributes to the certification easiness of the algorithm, potentially including but not limited to: - Data verification and assurance (zero-knowledge proofs for aircraft generated data download, etc.) - Explainability and predictability of the system (using LIME framework or similar) - Reduced time of retraining or new data incorporation to the model (KPI) **AI requirements:** AI models that 1) provide an easy-to-understand and easy-to-interpret output, 2) allow the continuous retraining or incorporation of new data, and 3) ensure the data custody chain from the data capturing system to the model

Use case 4_SPACE. Icing condition prediction
Partners: BAS
Description: Icing condition prediction for a region/vertiport using EO and historical aviation weather reports. **Industry challenge:** Weather conditions such as precipitation, winds, temperature, cloud ceiling have a direct impact on the performance and dynamics of an aircraft and in the operational scenarios for aviation. For this reason, several stakeholders of the ecosystem (pilots and air traffic controllers among them) need to check the real-time weather information (a.k.a nowcast) and the forecasted weather as part of their decision-making process during an operation (before taking off, landing, in-route, etc.). Decisions like vectoring, changes in the trajectory, etc can be usually taken to avoid unfavorable weather conditions. Inaccurate models can lead to reduced efficiency or contingencies during flights. **State-of-the-art:** Currently, both the spatial and temporal resolution of the weather information is limited, and the information provided by the airspace national service providers is many times wide range (i.e. with low updating rate and affecting to big spatial areas). This imposes a big limitation for frequent and small area located operations (like urban air mobility) and it leads on a conservative approach for assessing weather (i.e. avoid flying in the whole region if there is any risk) that limits the efficiency and scalability of this type of operations. **Expected impacts and outcomes:** The use of EO images combined with aviation weather reports to train an AI system is innovative per se, and it can have an impact on the aviation industry. To do that (and avoid false negatives that can lead to safety issues), the system needs to be trustworthy. Any potential improvement that can show (1) better accuracy of the current models and/or (2) better spatial and temporal resolution of the current models would be valuable. **AI requirements:** AI models that 1) ensure that the data is not tampered with and 2) show predictability in terms of false negatives

Use case 5_SPACE. Flood zone mapping
Partners: NR
Description: The objective is to establish an AI model for mapping flood-covered areas in Sentinel-1 and 2 satellite images. **Industry challenge:** Flood zone maps are essential for land-use planning and important in the municipalities' work with flood preparedness. The archive of flood-covered areas can also be used as calibration and validation data when starting to work with new flood susceptibility maps. **State-of-the-art:** The state-of-the-art method for detecting flood zones in satellite images is based on a time series of SAR images, where the event image is compared with a reference

image by calculating a difference image. Typically, the difference image is thresholded to detect potentially flooded areas. During the last decade, (DL)-based methods to analyse the time series have been explored, but acquiring sufficient training data is a challenge. **Expected impacts and outcomes:** Expected outcomes is a framework for analysing Sentinel-1 and –2 images for detecting flood zones based on a pre-trained foundation model. The number of false alarms and missing detection is lower than current state-of-the art methods. **AI requirements:** 1) Pre-trained multi-modal foundation models for multi-modal satellite data (both Sentinel1 and Sentinel-2 data). 2) AI model obtained by adapting the EO-specific foundation model to the specific task of flood zone mapping.

Use case 6_SPACE. Fast and accurate atmospheric Radiative Transfer (RT) simulations for satellite microwave instruments
Partners: CHALMERS
Description: The objective is to establish an AI model for mapping flood-covered areas in Sentinel-1 and 2 satellite images. **Industry challenge:** Using a reference Radiative Transfer Models (RTM) such as (Buehler et al., 2018), the challenge is to develop a system through machine learning which is capable to find accurate and fast solutions to the radiative transfer equation for the microwave and submillimetre region under realistic all-sky conditions. Similar to (Barlakas et al., 2022), this system should be compared to an operational RTM, e.g., (Saunders et al., 2018), to assess any improvement by machine learning. **State-of-the-art:** RTMs are necessary for some satellite- and ground-based measurements. The fundamental component of RTMs is a partial integro-differential equation, the radiative transfer equation. Models aimed at time-critical operational applications, such as weather forecasting, use physical simplifications and coarse discretization to obtain solutions efficiently at the expense of accuracy. The use of DL has been suggested as an alternative to the manual simplifications, e.g., (Stegmann et al., 2022). However, the complexity of the interaction between our atmosphere and the electromagnetic spectrum formulates a significant challenge that requires detailed inspection. In particular, at the microwave region, where several upcoming satellite instruments will measure hydrometeor properties characterized by non-spherical shapes, which are usually neglected to reduce the computational time, machine learning approaches are yet to be explored. **Expected impacts and outcomes:** 1 conference presentation; 1 scientific publication; An open-source software prototype that can be used by researchers and meteorological agencies to improve weather forecasting and, consequently, decision making. **AI requirements:** •Understanding the differences between fast and accurate RTMs, including the implications of the simplified physics from the fast RTMs. •Selection and compilation of the online observational data are required for assessing or developing the machine learning system. •Survey of physics-informed machine learning literature and related works. •Development of the described machine learning system with either pure supervised learning or more elaborate techniques, such as physics-informed machine learning. •Assessment of any advantage of the resulting system over conventional manual simplifications

Use case 7_SPACE. Generative models for 3D cloud fields
Partners: CHALMERS

Description: Development and evaluation of two generative models: an unconditional generative model and a conditional one. The emphasis would be in investigating diffusion models given its recent success, but any generative model, including Generative Adversarial Networks (GANs), can be considered. **Industry challenge:** The models would be trained using CloudSat as a reference data, and the conditional model should only use public hyperspectral data. The models should, ideally, be able to generate 3D cloud fields, as opposed to the 2D cloud fields observed by CloudSat. The main challenge is, thus, to investigate if advances in the field of generative modelling can offer a better performance than the model presented in (Leinonen et al., 2019) as well as joint stochastic 3D retrievals of atmospheric cloud fields. Any satellite data to be used is publicly available. **State-of-the-art:** The CloudSat satellite has been the gold standard for obtaining cloud vertical structures on a global scale. However, limitations in the satellite orbit and instrument hinder the use of CloudSat data for satellite data simulators that need 2D or 3D atmospheric input data. Leinonen et al. (Leinonen et al., 2019) studied the reconstruction of cloud fields using a conditional GANs trained against CloudSat data and conditioned on MODIS observations and auxiliary data, e.g., forecast data. They highlight limitations of their approach. GANs catalysed the interest of the scientific community to push the development and application of generative models where, for example, diffusion models have arisen as a popular alternative to GANs. Generative models are yet to be exploited for generating atmospheric cloud fields. **Expected impacts and outcomes:** 1 conference presentation. 1 scientific publication. An open-sourced generative model that can be used by researchers to simulate 2D and 3D cloud fields. **AI requirements:** •Survey of generative models for atmospheric applications and development of the two models described above. •Survey of conventional cloud field reconstruction algorithms to be used for future satellite missions (Barker et al., 2011). •Selection of the satellite data to be used, publicly available. •Ensure the physical realism of the machine learning models. •Comparison of the developed conditional generative model with a discriminative model, which offers marginal distributions (Amell et al., 2023).

Use case 8_SPACE. Cost-effective precipitation retrievals
Partners: CHALMERS
Description: **Industry challenge:** The challenge consists of analysing the shortcomings of (Amell et al., 2023) with a focus on exploring an inexpensive neural network architecture that offers at least a similar performance as the Convolutional Neural Network (CNN) used in (Amell et al., 2023) and which offers a case-specific retrieval error. Africa should be included in the area supported for the retrievals, with the possibility to extend them to the full disc. A training dataset will be assembled consisting of Meteosat infrared observations labelled with the latest precipitation rate estimates from the Global Precipitation Measurement Core Observatory. **State-of-the-art:** Works such as the one proposed in (Pfreundschuh et al., 2022) have highlighted the advantages of machine learning approaches to the retrieval of precipitation, i.e., historical estimation of precipitation rates, over conventional approaches when considering satellite imagery. Pfreundschuh et al. presented in (Pfreundschuh et al., 2018) a method for atmospheric retrievals, which is an alternative to flexible but expensive statistical approaches. This method can describe the uncertainty in the retrieval due to data variability, eliminating the need for ensemble predictions. Using the method from (Pfreundschuh et al., 2018), Amell et al. presented in (Amell et al., 2023) a similar approach to (Pfreundschuh et al., 2022) but where only the European geostationary

satellite was used. In this case, they focused only on the effectivity of the neural-network retrieval but not its efficiency, thus requires non-minimal computational resources to run inference for example the whole African continent. Furthermore, they solely targeted Africa despite the satellite covers a larger area and did not use any time dimension.
Expected impacts and outcomes: 1 conference presentation. 1 scientific publication. An open-sourced retrieval model that can be used by the scientific community to obtain precipitation estimates efficiently from the European geostationary satellite.
AI requirements:
•Compilation of neural network architectures that have a small computational footprint.
•Training and comparison of the performance of such neural network models.
•Assessment of the difficulty to incorporate the temporal domain in the retrievals through, e.g., autoregressive models, Recurrent Neural Networks (RNNs) or semi-supervised learning, while maintaining a small computational footprint.
•Formal evaluation of the distributions retrieved with the method presented in (Pfreundschuh et al., 2018) to assess whether alternative methods, e.g., predicting distribution parameters from a family of distributions, offers a more efficient retrieval without degrading performance.
•Validation of the retrievals against independent datasets, coming from other retrieval schemes, accumulated rain, or sub-hourly rain rate estimates. The latter can be difficult to accomplish due to the availability of suitable data.

Use case 9_(AERO)SPACE. Foreign object debris (FOD) detection

Partners: BAS

Description: Foreign object debris (FOD) detection for landing hazard avoidance in final approach and takeoff areas (FATO)
Industry challenge: As part of autonomous landing applications, a system needs to be capable of detecting that there is a hazard in the landing zone to avoid any safety concern. Many aircraft and/helicopters use tires or skids that can be damaged if an object is in the runaway or in the landing zone and even create an accident if not corrected before starting the landing process.
State-of-the-art: Currently, FOD detection is normally performed both by the ground crew and the pilot on board, relying on visual methods. Artificial vision use for FOD detection is one of the archetypical use cases of image processing in the aviation industry. This is especially relevant for autonomous vehicles and operations, where a pilot is not on board and the frequency of operations is expected to be really high. So, automation of this process is critical for enabling these markets.
Expected impacts and outcomes:
Contributions that ensure that the data has not been tampered (KPI) and that increase the accuracy of the image processing algorithm (KPI). Besides, explainable AI frameworks will be helpful to enable an easier certification process, showing how the system works to the regulator and the potential outputs that it can have.
AI requirements: AI models that 1) shows in an intuitive way how they work to a regulator, 2) shows that the data has not been tampered from the sensor to the inference model and 3) shows that the training data used has not been adulterated by anyone.

Use case 10_(AERO)SPACE. Automatic Speech Recognition (ASR) for automatic callsign detection on ATC voice communications

Partners: BAS

Description: The main means of communication between an air traffic controller and a pilot in aviation is via voice communication (normally, over a Very High Frequency (VHF) radio). **Industry challenge:** In high congestion scenarios (like in the surroundings of big airports), the amount of chatter and conversations is drastically high, making sometimes hard for the pilot to identify when the Air Traffic Controller (ATC) is talking to him/her. Each message from the ATC controller starts with the callsign (unique identifier) of the aircraft that is directed at. The challenge is to create tools that allow to reduce the chatter or support the pilot to understand if the message is directed to him/her or other pilot in the area. **State-of-the-art:** Currently, natural language processing or Automatic Speech Recognition (ASR) techniques have not been applied in aviation, even as supportive tools. The main issue for not adopting these technologies is the lack of tools for ensuring data completeness and representativeness, generalizability of the model (understood as the capacity of a machine learning model to keep an acceptable level of performance on unseen input data) and robustness and stability of the models. **Expected impacts and outcomes:** In addition to demonstrate the capabilities of a model to detect callsigns in an ATC voice communication record (based on available resource and models), it is expected that this use case can contribute to automatically extract robustness and stability metrics of the model and explainable tools that helps the regulator to understand that the data used for training is representative and complete. In addition, the possibility of including reinforced learning (by the pilot itself) would be valuable. **AI requirements:** AI models that 1) automatically extract stability and robustness metrics for nominal and corner cases, 2) show graphically the characteristics of the training data, and 3) allow reinforcement based on the inputs of a pilot/operator.

Use case 11_SPACE. Monitoring of maritime illegal activities
Partners: ECoE
Description: Maritime industry often suffers from illegal activities such as fishing near to coral reefs that results to ocean biodiversity destruction, immigration of people, oil spills from ships and illegal shipping. Satellite Remote Sensing images and especially those derived from SAR sensors are advancing the monitoring of the aforementioned illegal activities among others. Automatic Identification System (AIS) has also enhanced those applications. AIS is installed in commercial ships over 300 gross tons and all the passenger ships thus small ships, fishing boats and military vessels are not required to have installed AIS transponders. The certain goal of this use case is the detection of illegal activities in the Mediterranean Region by detecting ships on SAR images and verifying their legal/illegal status using AIS MarineTraffic API. For example, detected fishing boats near coral reefs during a prohibited period. This certain application can be useful for the corresponding stakeholders (e.g., governmental bodies, marine and maritime companies, etc.) **Industry challenge:** Detection of small vessels is still challenging due to the resolution of open-access satellite data. Monitoring the trajectory of vessels through satellite images is also challenging. Expanding AI models with training on new available data in a regular basis can be beneficial. Furthermore, the development of lite AI models for real-time or near real-time applications can also be helpful. **State-of-the-art:** In maritime monitoring, and more specific for ship detection tasks, YOLO-based methodologies are employed. A variation of YOLO algorithm, named CYSDM succeed to outperform YOLOv5s by achieving an accuracy of 98.68%, 9.07% higher than ordinary YOLOv5s, trained on infrared images and detecting ships in uncertain oceanic environments (L. Li et al., 2022). Moreover, there are also adaptations of the YOLO framework to create lightweight deep learning models for on-board ship detection to enhance the real-time monitoring of maritime traffic

like Lite-YOLOv5(Xu et al., 2022) and YOLOv7-Ship (Jiang et al., 2024). Using SAR data for ship detection most of the time suffer from strong scattering, background interference, strong sparseness, etc. Thus, novel models are combining transformer mechanisms and CNNs. Such a model is the CRTransSAR which is using the global contextual information extracting capabilities of transformer-based models and the local adaptability of CNNs for ship detection. During the validation of this model on a benchmark dataset, achieved an accuracy of 97%(Xia et al., 2022). Other strategies like the few-shot object detection on remote sensing imagery are also employed for ship detection (X. Li et al., 2022). Another novel model is the Multiscale Pyramid Attention Model (MPAM). MPAM, at its core consists of deep feature extraction submodules (DFES), channel multilayer attention fusion submodules (CMAFS), and spatial multilayer attention fusion submodules (SMAFS). DFES at first, divides the feature map into different levels and then CMAFS and SMAFS are used to fuse channel and spatial attention blocks on feature maps to extract relevant features to enhance feature representation. This model, outperformed state of the art model like Faster-R-CNN, RetinaNet and YOLOv3 (Wang et al., 2024).

Expected impacts and outcomes: 1 Journal publication. 1 Algorithm.

AI requirements: This use case should employ state-of-the-art AI methodologies and algorithms such as attention mechanisms, convolutional neural networks and pre-trained models. Furthermore, the utilization of transfer learning strategies can also be beneficial. Sentinel-1 and Sentinel-2 open-access data can be used for such tasks. Furthermore, the use of PlanetScope data (limited open access for research and education purposes) can enhance this use case results. This task will need a sufficient amount of processing units and storage for the development, tuning, and training of the models, as well as for their evaluation.

Use case 12_SPACE. Forecasting soil water availability for monitoring illegal abstractions

Partners: ECoE

Description:

The scope is to use an AI-based methodology to forecast the soil water availability. Specifically, the application aims to develop an advanced tool dedicated to forecasting soil water availability while focusing on the imperative of real-time monitoring for detecting illegal abstractions such as unauthorized groundwater pumping and river diversions. Through a systematic comparison of forecasted and nowcasted availability, the developed model will discern whether agricultural parcels receive more water than the calculated requirement, facilitating proactive management and sustainable water use in the agricultural landscape. Farmers, farming companies, and relevant governmental bodies can benefit from this methodology/model.

Industry challenge: The agriculture industry around the world suffers from climate change. Water-scarce areas are suffering from irrigation water shortages due to drought events. Moreover, in areas like Cyprus, it is noticed that farmers who are cultivating rainfed crops are illegally using more water for irrigation purposes.

State-of-the-art:

Remote Sensing and EO are widely used in irrigation management in order to retrieve useful information about the cultivated crop types and their current crop growth stage. By combining this information with evapotranspiration rates, the amount of irrigation needs can be calculated (Manivasagam, 2024; Pande et al., 2023; Roy et al., 2023). Furthermore, by monitoring the spatiotemporal patterns of soil moisture using spaceborne sensors the detection of irrigation events can be determined (Bazzi et al., 2022; Zappa et al., 2021). The employment of Remote Sensing for the detection and monitoring of potential illegal abstractions is still unexplored. Still, a recent research work showed that by monitoring the vegetation health using satellite vegetation indices and by observing unusual patterns of healthy vegetation can be beneficial for the detection of potential illegal water abstractions or illegal irrigation activities (Venegas Quiñones et al., 2024).

Expected impacts and outcomes: 1 journal publication. 1 Methodology. 1 Algorithm. **AI requirements:** This use case should employ state-of-the-art AI methodologies and algorithms for time-series processing and forecasting. Data from in-situ meteorological networks, Copernicus Atmosphere Monitoring Service (CAMS), Copernicus Climate Change Services (C3S), NASA's MODIS satellite spectroradiometer, NASA's GPM and EUMETSAT satellites can be fused for the implementation of the use case. This task will need a sufficient amount of processing units and storage for the development, tuning and training of the models, as also for their evaluation.

6 Conclusions

In conclusion, this deliverable has given a thorough and informative summary of the main challenges faced in the four designated verticals – energy, healthcare, manufacturing, and space - but it has also given important background information, thorough applications of AI, and insights into novel challenges that are unique to each of these domains.

- Energy: a total of 14 challenges have been identified with the energy sector, encompassing areas such as energy integration, grid optimization, energy efficiency, and sustainability.
- Healthcare: a total of 15 challenges have been identified in this vertical, including patient monitoring, the direct effect of a treatment, and risk or outcomes prediction.
- Manufacturing: a total of 6 challenges have been addressed, spanning areas such as sustainable manufacturing, condition-based maintenance, and optimization of the production in terms of configuration, scalability, and efficiency.
- Space: 12 challenges have been identified for this vertical, including satellite communication, atmospheric events simulation, and agricultural, natural disasters and maritime monitoring.

These challenges can all be attributed to one or more of the four fundamental pillars that serve as guidelines for the responsible development and application of artificial intelligence: green AI, adaptive AI, human-centric AI, and trustworthy AI. However, the list of challenges provided is still temporary and the partners involved are dedicated to continuous improvement and iteration. To find a homogeneous covering for each challenge, workshops covering the mapping between verticals and pillars are being organized. Through cooperative exchange among participants, these workshops will help in finding common ground, resolve areas of overlap, and guarantee that all use cases are covered in the context of Green AI, Adaptive AI, Human-centric AI, and Trustworthy AI.

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