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A 3D indicator for guiding AI applications in the energy sector

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A R T I C L E I N F O

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A B S T R A C T

The utilisation of Artificial Intelligence (AI) applications in the energy sector is gaining momentum, with increasingly intensive search for suitable, high-quality and trustworthy solutions that displayed promising results in research. The growing interest comes from decision makers of both the industry and policy domains, searching for applications to increase companies' profitability, raise efficiency and facilitate the energy transition. This paper aims to provide a novel three-dimensional (3D) indicator for AI applications in the energy sector, based on their respective maturity level, regulatory risks and potential benefits. Case studies are used to exemplify the application of the 3D indicator, showcasing how the developed framework can be used to filter promising AI applications eligible for governmental funding or business development. In addition, the 3D indicator is used to rank AI applications considering different stakeholder preferences (risk-avoidance, profit-seeking, balanced). These results allow AI applications to be better categorised in the face of rapidly emerging national and intergovernmental AI strategies and regulations that constrain the use of AI applications in critical infrastructures.

1. Background

Digitalisation in the energy sector is driven by an increasing availability of data, computing power and digital technologies, and the need for enhanced pattern analysis and planning [1]. With the overall goal to improve system efficiency, the movement towards digitalised systems is also supported through AI applications, which can help lower costs, reduce energy losses and accelerate the integration of renewable energies into electricity grids [2]. Although it is difficult to estimate the added value of AI applications, they can help minimise investments in assets, reduce peak energy demands or exploit flexibility in energy systems which could lead to billions of dollars in savings [3].

The term AI can be subject to misinterpretation, as it is often used interchangeably with Machine Learning (ML), data science, Internet of Things (IoT) or big data [4,5]. In reality, AI can be viewed as the umbrella term describing the goal of making computers solve problems like human beings would. Within the vast field of AI, machine learning and its sub-parts are tools with which algorithms can be built, and big data from interconnected sensors, the so called Internet of Things (IoT), are the fuel feeding enhanced computational models, eventually providing decision support to analyse and manage complex systems or behaviours. ML can be viewed as the process of estimating models to reflect real-world problems, generally based on data sets, enabling human understanding of complex systems through data [6]. Fig. 1 shows how AI applications can be categorised in terms of their use cases in the energy sector, with various examples for each sub-part. Here, AI can be seen as an overarching term containing all of the described taxonomy of ML.

Within the modern context of the energy transition and the reshaping of the energy sector from centralised to more distributed systems, digitalisation will be instrumental in the implementation of reliable, cost-effective electrification. With the rapid integration of renewable energy in the electricity grid (additional installed capacity of 280 GW globally in 2020, up 45% compared to 2019 [7]), AI can be seen as a

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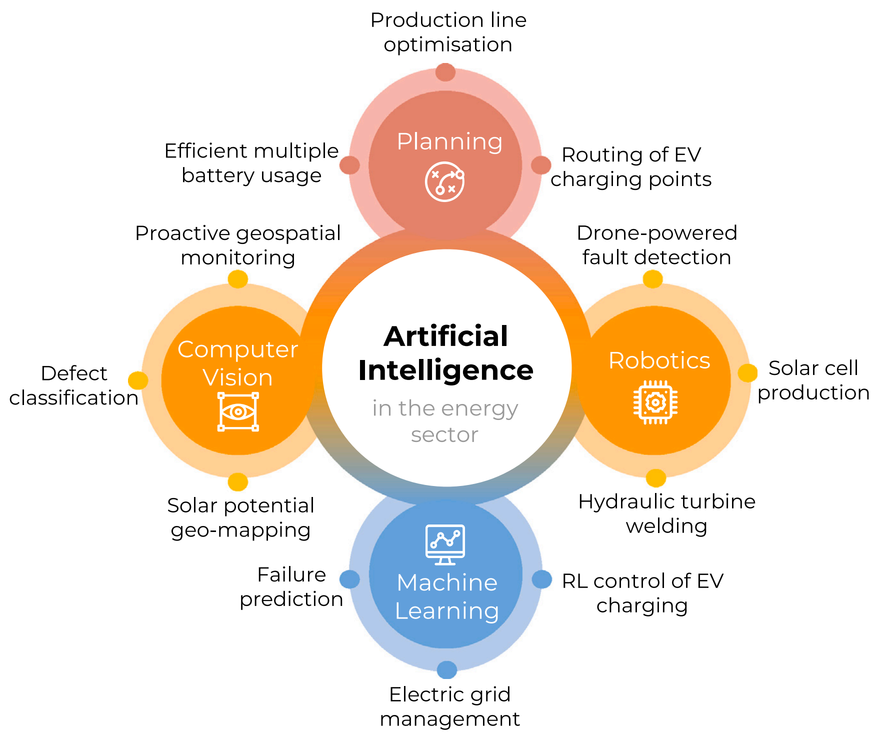

Fig. 1. Proposed AI taxonomy for applications in the energy sector, with example use cases.

tool of digitalisation, and will play a vital role in redesigning future energy systems and the energy system supply chain (see Fig. 2D), from accurate forecasting and planning of non-programmable renewable energy sources, grid operation and optimisation, demand-side managements, and automated intelligent fault detection [8,9]. Recent AI advances therefore permeate every level of energy systems, from retail, distribution, transmission grid planning and operation as well as generation [5]. Indeed, more and more countries develop and test AI applications in energy systems [10]. For example in the US, in parallel to the establishment of an Artificial Intelligence and Technology Office [11], the Department of Energy provided $20 million funding for innovative research of AI in 2019 [12].

Fig. 2 summarises key figures for AI and big data: Fig. 2A shows the annual number of AI publications grouped by AI cluster until 2018 [4], and Fig. 2B shows the forecasted annual stock of connected devices (including smart meters, sensors and other IoT devices) up to 2030 [13]. Over the last five years, the deployment of smart devices grew by ~33% per year to reach 9 billion in 2021 [7]. The parallel increases in data availability from smart meters and research developments in AI is expected to continue, as the demand for efficient methodologies to analyse data and extract meaningful information grows [7].

In such a fast-moving field, one challenge is to ensure knowledge transfer between research, industry and policy. Policy makers and regulators are becoming aware of the potential risks AI applications may add to the safe operation of the energy sector. As highlighted by the recent AI strategy proposal from the European Commission (EC) [14] and national strategies report [15] (see Fig. 2C for the timeline of the newly proposed EU AI Act), the European Union pursues a harmonised regulation which is seen as vital for safe AI applications that are also compliant with fundamental citizen rights. Indeed, consistent and uniform national rules can help prevent fragmentation of markets and increase legal certainty for operators of AI applications [16,17].

With the rise of AI applications in various industries, classification and comparison schemes emerged that allowed one to relate existing applications one to another. It is therefore noteworthy to compare recent AI frameworks with the proposed 3D indicator, to further highlight its relevance. Fig. 3 shows a table summarising the main characteristics of five other frameworks [18–22]. The Organisation for Economic Co-operation and Development (OECD) proposed one of these frameworks for the classification of AI systems [18], which is primarily aimed at policy makers, is more complex than the indicator proposed in this paper, and requires detailed analyses across a large number of dimensions (i.e., People & Planet; Economic Context; Data & Input; AI model; and Task & Output). Its level of detail makes it less synoptic and more difficult for non-experts to apply. McKinsey Global Institute designed a business oriented framework to assess the economic potential of AI techniques [19], with specific focus on deep learning applications which limits the applicability of the methodology. Lee et al. propose innovative frameworks to assess the energy savings potential of AI applications [20,21], which in theory can be extended to other industries and sectors, however the methodology lacks clear actionable outputs. Therefore, no overarching, flexible method has been proposed so far, with wide target audience, high applicability potential and actionable insights. The proposed 3D indicator aims to fill this gap, while also allowing the introduction of weights such as economic benefit or regulatory risk, in order to differentiate the diverging decision criteria sets from policy makers and companies.

There also exist other classification schemes in the literature which focus on the comparison of AI models [23–25]. For example, the work of Bahrammirzaee [23] compares artificial neural networks, expert systems and hybrid intelligence systems applications in the financial sector, using three categories (application domain, algorithm and performance). Likewise, from the perspective of the health sector, Nsoesie [24] argues that performance, input data and algorithms, as well as annotation needs are fundamental categories to evaluate the benefits of AI applications. For the energy sector, Antonopoulos et al. [25] reviews AI applications to the sub-field of demand response. In the latter study, the comparison of AI applications builds on algorithm choice and targeted problems within multiple demand response studies.

Hence, the main objectives of this paper are:

1. Providing a framework to identify the most promising AI applications in the energy sector.

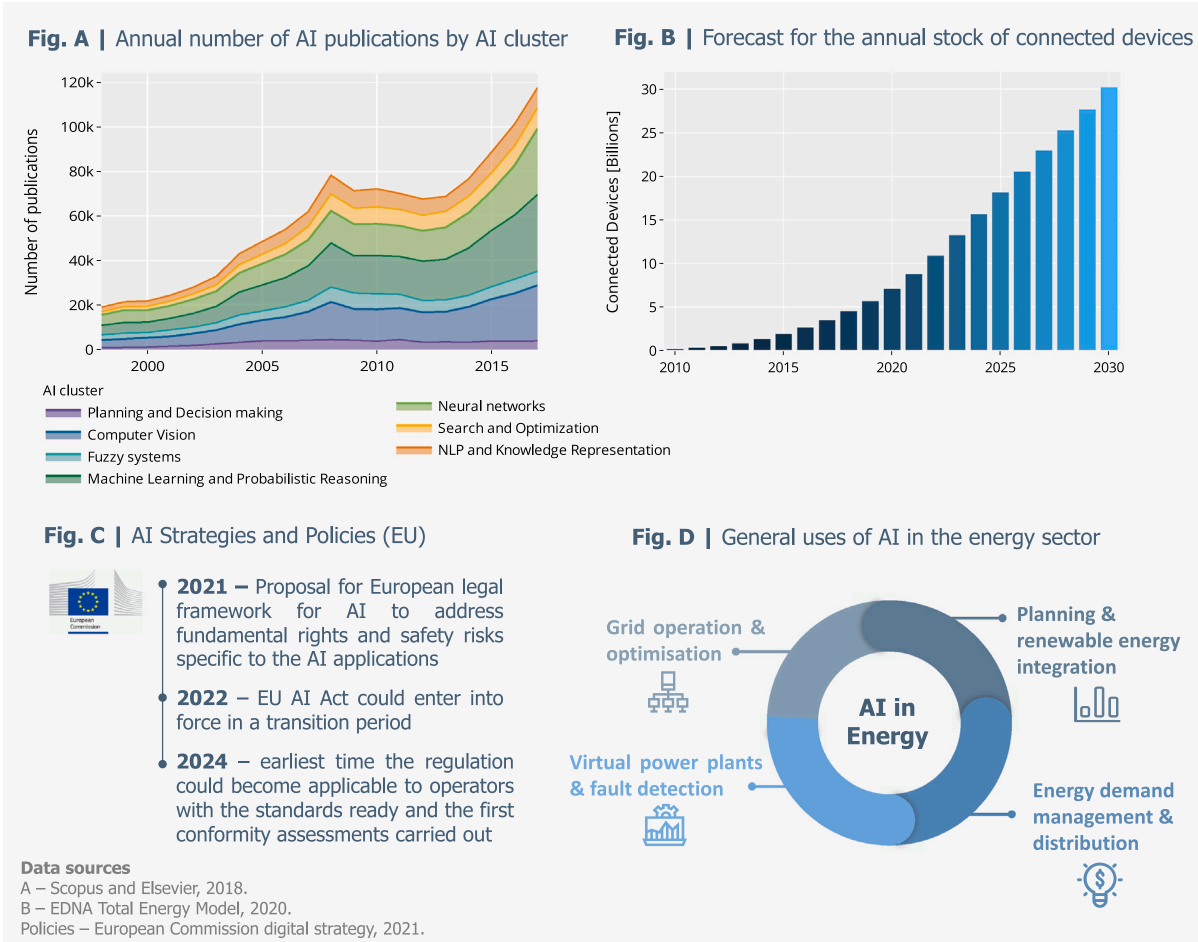

Fig. 2. AI and big data in energy — key figures highlighting the parallel increase in smart device data availability and research developments in AI, the EC new regulatory proposals and different uses of AI in the energy sector supply chain.

2. Applying the flexible framework to categorise and compare a set of identified AI applications in terms of economic benefits, maturity and regulatory risk potentials.
3. Test different weighting schemes that reflect the diverging preferences from business developers (high maturity and benefits of applications) and policy makers (low regulatory risk and societal benefits).

To this end, we introduce a novel, three-dimensional indicator that can help visualise and classify AI applications with respect to their potential for the energy system transformation. The proposed approach both addresses potential benefits and risks of AI, in line with recent research on such aspects [26,27]. The 3D indicator can therefore be a valuable decision support for screening AI applications with regard to their interest for businesses and policy makers.

This paper will be structured in the following way: firstly, Section 2 will focus on how digitalisation is driving the growth of AI applications, and how the new European legislative proposal aims to tackle the risks and challenges surrounding AI. Section 3 will introduce a novel indicator for AI applications to describe their maturity level, potential and risks, as well as a ranking method based on the three scales. Section 4 presents the various applications of AI in the energy sector through case studies, highlighting the applicability and relevance of the developed 3D indicator. Section 5 gives the main results, and Section 6 will provide a discussion of the indicator findings. Finally Section 7 will give a summary of key insights and an outlook of future research.

2. Risks, potential and AI policy landscape

AI technology has become a focus in the digitalisation of the energy sector, as growing amounts of data from smart meters to grid operators drive the need for efficient analysis solutions. For utilities, digitalisation is expected to reduce operating expenses by up to 25% and deliver performance gains of 20% to 40% in areas such as safety, reliability, and customer satisfaction [28]. To achieve such perspectives, it is argued that AI should become an integral part of business strategies, as a means to provide useful, additional insights and beneficial, economic results of increased systemic or process efficiency.

The surge in AI has placed it at the forefront of research, industry and more recently policy making. Along with the rapidly evolving models and algorithms, a shift from human-controlled data inputs to fully automated computer-led AI applications, at times, with independent decision making, is underway [4,6]. At the same time, questions such as explainability, transparency and bias are gaining attention in the regulatory landscape, alongside the general issues of cyber-security and regulatory compliance. The general risk related to AI solutions lies in the model used, and more specifically the ability to verify the decisions of algorithms. Today, this risk is mainly linked to the use of approximation functions, such as neural networks, which can create 'black box' outcomes. While such neural networks allow approximating complex and non-linear functions for problems solving, the explainability of outputs and thus their proper operation is often hard to control. In the long term, their use tends to become more widespread, leading to a probable increase in the level of risk of AI applications. Although a wide range of values exist depending on the survey, 10–25% of companies

AI frameworks	Target audience: Industry	Target audience: Policymakers	Target audience: Research	Framework goal	Input data requirements	Applicability to all AI sectors	Actionable visual output
OECD Framework for the classification of AI systems OECD (2022) [18]	○	●	○	Characterise AI systems from a policy perspective, to help develop policies and regulations.	High	✓	✗
McKinsey Global Institute AI frontiers insights Chui et al. (2018) [19]	●	○	○	Assess the economic potential of advanced AI techniques across industries and business functions.	Medium	✗	✗
Universal workflow of AI for energy savings + AI implementation framework development for building energy savings Lee et al. (2022) [20], Lee et al. (2020) [21]	●	○	●	Identify workable AI technologies for energy saving. Develop a framework for deploying AI-assisted control at for building energy savings.	Medium	✓	✗
Implementation of AI: Roadmap for Business Model Innovation Reim et al. (2020) [22]	●	○	○	Develop a roadmap to guide the implementation of AI to firm's operations.	Low	✓	✗
Proposed 3D indicator for guiding AI applications in the energy sector This work	●	●	●	Characterise and classify promising AI applications for stakeholders through a 3D indicator-based framework.	Low	✓	✓

Fig. 3. Comparative table of the main characteristics of five recent AI frameworks [18–22] and the proposed 3D indicator. Target audience: intended framework users and stakeholders; Framework goals: brief summary of the main objectives; Input data requirements: indication of the overall input data complexity; Applicability to all AI sectors: framework generalisability; Actionable visual outputs: presence of specific formats for simple, informative outputs.

worldwide have already introduced AI applications [29], with most of the surveyed companies already considering the integration of AI in their systems and processes or at least future AI pilot projects [30].

The European Union (EU) aims at becoming a leader both in terms of AI employment strategies and legal framework propositions [15], in line with its overall ambition to leverage digital technology advances towards a human-centric, sustainable and resource-efficient future [31–34]. The new AI regulation proposal, known as the EU AI Act (see Fig. 2C), is part of this new paradigm, following a two-fold goal of preparing the ground for both high quality and trustworthy AI applications. The European Commission proposes a set of rules and sanctions to address the specific risks posed by the use of AI [14,15]. The proposed rules have the following objectives:

- ensure safety and respect of existing law on fundamental rights for AI applications placed/used on the Union market.
- ensure legal certainty to promote innovation and investment in AI.
- facilitate the development of a unified market for trustworthy AI applications, and prevent market fragmentation.

The harmonised rules follow a proportionate risk-based approach, whereby AI applications are classified via a risk-based scale. AI applications that pose high risks to the health and safety or fundamental rights of persons will have to comply with mandatory requirements for trustworthy AI, as well as follow conformity assessment procedures before being placed on the market (for example, all remote biometric identification systems are considered high risk and subject to strict requirements). This approach aims to cover issues such as data quality, data privacy, transparency and provision of information to users, human oversight, robustness, accuracy and cybersecurity. According to Niet et al. [35], one of the first studies to link AI governance and risks in electricity systems, the EU AI Act is a step in the right direction in addressing transparency and the division of responsibilities in AI applications, but under-emphasises risks related to human autonomy, cybersecurity, market dominance and price manipulation, which would be amended through additional guidelines for system operators and the electricity market.

With regards to the energy sector specifically, AI applications face additional barriers related to knowledge transfer between academia and industry [29,36,37]. Especially in a highly technical field with vast industry applications such as AI, close collaboration and clear communication is necessary to boost innovation performance [38]. Common challenges and barriers for research to industry pathways are the following:

- *lack of big data infrastructure* – industries are not always technologically ready for handling and accessing big data, and concerns over data ownership, privacy and cybersecurity also need to be addressed [39], especially in the energy field with the boom in smart metering technologies.
- *conflicting project planning and output expectations* – industries often rely on short term projects and outcomes to maintain leadership in the market, with commercial goals that can go against the pace of research institutions, who tend to strive for steady income streams and long-term projects [40].
- *resource discrepancies* – funding and resource sharing is a key aspect for successful transitions from research to industry, and program like Horizon Europe can pave the way with objective-driven partnerships [41].

It is important to note that AI applications can often be developed as a collaboration between industry partners and academia, and studies have shown that this is an effective way to establish effective knowledge exchange [42–44]. On the research side, advantages of such collaborations include access to industry funding, equipment and patenting, leveraging industry experience on requirements and future uses of AI applications, and potential commercialisation of these tools. Moreover, industrial partners gain access to research infrastructure and high-quality talent, as well as a way to externalise exploration studies for innovative ideas with direct applications in industry.

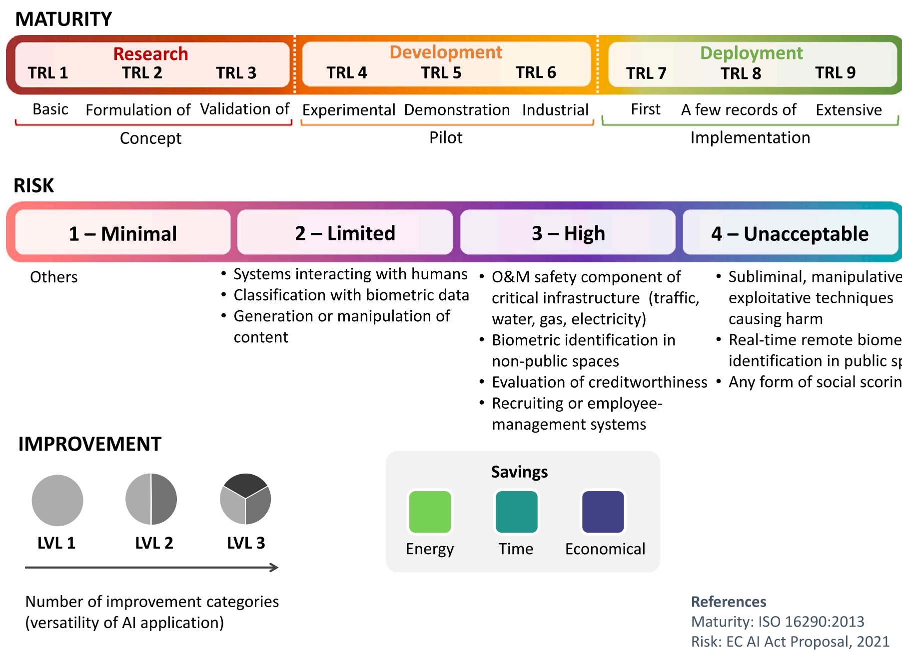

Fig. 4. Summarised guidelines for the maturity, risk and improvement scales, which can be used as a reference point to categorise AI applications. The maturity indicator follows the established TRL standard [45], and the risk level is based on the newly proposed EC scale [14]. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

In summary, the new emerging policy landscapes and shifting industry goals create the need for clear communication and comparison mechanisms for AI applications. In the next section, a novel three dimensional indicator is proposed to help navigate these new challenges, inspired by the EC risk-based approach for AI, the research to industry bottlenecks and potential of AI solutions to accelerate the energy transition.

3. Proposed novel AI indicator

As a response to the rapidly changing employment of AI and its regulations, this paper proposes a novel indicator to visually classify AI applications in the energy sector for industry, research and policy makers alike. Its objective is to provide a common, simple comparative baseline to visualise the relative position of AI applications with regards to three key parameters. As illustrated in Fig. 4, the three-dimensional indicator is as follows:

- Maturity is inspired by the Technology Readiness Level (TRL) scale [45,46] to reflect the project's current state of market integration. The progression from research to deployment, through early pilot projects, maps the evolution from low to high level market penetration. As seen in Fig. 4, the maturity level follows a 9 point scale, separated into three main stages: research (concept design), development (pilot creation) and deployment (industry implementation).
- Risk refers to the newly proposed European legal framework for AI, the EU AI Act, introduced in Section 2. This indicator aims to ensure the safety, reliability and transparency of AI applications. As seen in Fig. 4, four risk levels are identified: unacceptable, high, limited and minimal. In order to classify AI applications within this risk scale, key identifying points are included below each level. For example, AI applications deemed unacceptable in terms of risk level are those which aim to manipulate human behaviour, classify through any kind of social score or use real-time biometric identification. High risk AI applications for the energy sector are those which are designed as safety components for critical infrastructure (road traffic, supply of water, gas, heating and electricity), where failures or malfunctions may put people at risk or lead to disruptions in social and economic activities.
- Improvement indicates the versatility of potential gains from AI applications. Given that improvement can cover different aspects, such as energy, time or economical savings, a three-level scale is proposed which highlights the number of improvement categories for a given AI application, as seen in Fig. 4. The focus here is on these three specific savings (i.e., energy, time and economical) as they are relevant to all AI applications in the energy sector, but other aspect could easily be added or considered. The colour map then enables to distinguish the type of savings. Quantifying AI application gains is complex as they can cover a multitude of metrics, so this simple qualitative indicator serves as a proxy to visualise the impact level and versatility of AI technologies, while not specifying the magnitude, which are not necessarily comparable between AI applications. For example, time savings take different forms according to each application: it may refer to faster processes, decision making and/or computation times, as compared to non-AI methods.

This three-dimensional indicator illustrates at a glance the main potentials and challenges for the integration of AI in research and industrial applications. Fig. 5 shows an example application of the indicator with classified use cases of AI applications in the energy sector. The figure is created by placing the risk level on the abscissa, the maturity level on the ordinate, and representing each AI point with the developed improvement visual indicator (see Fig. 4). The next section will detail the various AI applications and their placement within the three-dimensional space.

In addition, a sensitivity analysis based on the proposed indicator is presented, enabling the ranking of AI applications with respect to the three dimensions for different scenarios. The ranking is established using a variation of the Manhattan distance as metric, which essentially is the sum of absolute differences between the measures in all dimensions from the optimal value. In this case, different weights are assigned to the three indicator scales, reflecting various scenarios:

$$D = \omega_1 \cdot \frac{|9 - \mathrm{TRL}|}{8} + \omega_2 \cdot \frac{|1 - R_s|}{3} + \omega_3 \cdot \frac{|3 - I_s|}{2} \quad (1)$$

where $D \in [0, 1]^{\mathbb{R}}$ is the AI application score for which the optimum is 0 as it represents the weighted distance from optimal values in

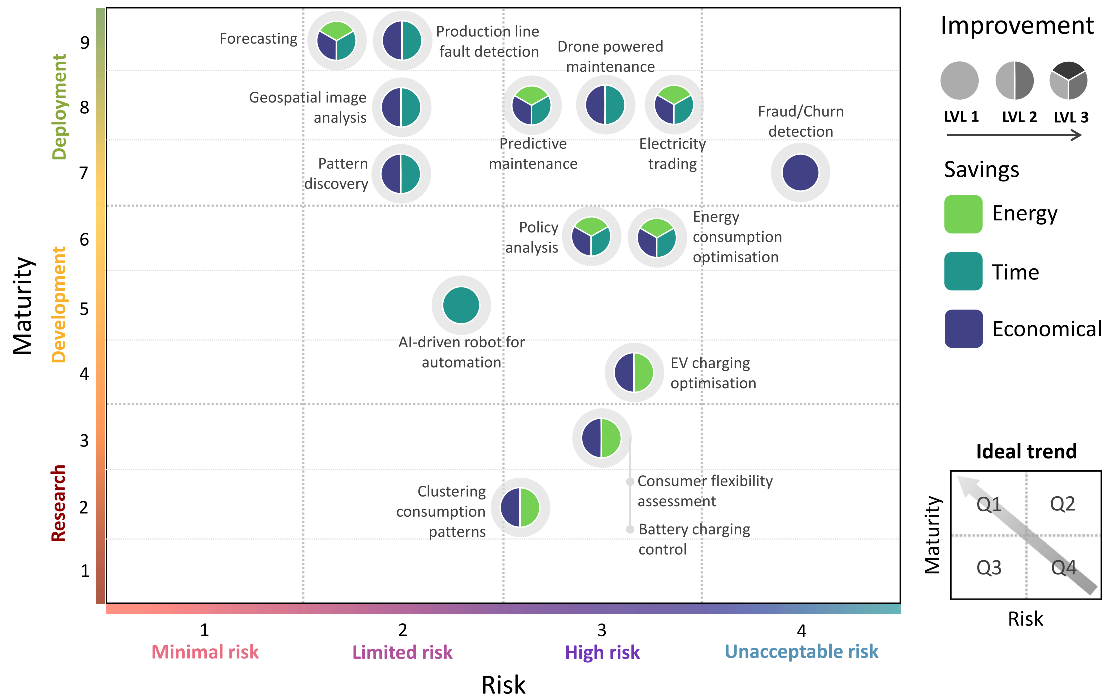

Fig. 5. Visual representation of the novel three-dimensional indicator classification for the presented case studies. The abscissa is the EC proposed risk scale, the ordinate is the TRL maturity scale, and the scatter plot markers indicate the AI application versatility for the improvement scale. Key quadrants and the ideal trend are shown as a sub-figure on the bottom right.

Table 1
Exemplary AI application use cases using the 3D indicator.

AI application	AI subgroup[a]	Maturity	Risk	Improvement			Sources
		TRL[b]	EC Scale[c]	Energy	Time	Economical	
Forecasting	SL	9	Limited	●	●	●	[47–56]
Energy consumption optimisation	SL	6	High	●	●	●	[57–60]
Predictive maintenance	SL	8	High	●	●	●	[61–64]
Fraud/Churn detection	SL	7	Unacceptable	○	○	●	[65–67]
Battery charging control	RL	3	High	●	○	●	[68–73]
EV charging optimisation	RL/UL	4	High	●	○	●	[74–79]
Electricity trading	RL	8	High	●	●	●	[80–85]
Clustering consumption patterns	UL	2	High	●	○	●	[86–91]
Consumer flexibility assessment	UL	3	High	●	○	●	[92,93]
Pattern discovery	SL/UL	7	Limited	○	●	●	[94–97]
Policy analysis	SL/UL/RL	6	High	●	●	●	[98–101]
Geospatial image analysis	CV	8	Limited	○	●	●	[102–104]
Production line fault detection	CV	9	Limited	○	●	●	[105–107]
AI-driven robot for automation	RB	5	Limited	○	●	○	[108–110]
Drone-powered maintenance	RB	8	High	○	●	●	[111–117]

[a]Supervised Learning (SL), Unsupervised Learning (UL), Reinforcement Learning (RL), Computer Vision (CV), Robotics (RB).
[b]Technology Readiness Level scale: 1–3 Research, 4–6 Development, 7–9 Deployment.
[c]European Commission AI risk scale: Unacceptable, High, Limited, Minimal.

each indicator. The variables TRL, $R_s, I_s \in \mathbb{N}$ are the indicator scores, where TRL $\in [1,9]^{\mathbb{N}}$ is the maturity level (optimum is 9), $R_s \in [1,4]^{\mathbb{N}}$ is the risk score (from 1=minimal to 4=unacceptable, with the optimum at 1), and $I_s \in [1,3]^{\mathbb{N}}$ the improvement score reflecting the AI application savings versatility (optimum is 3). The weights $\omega_\alpha \in [0,1]^{\mathbb{R}}$, $\alpha = 1,2,3$, $\sum_{\alpha=1}^{3} \omega_\alpha = 1$, are associated respectively to the maturity, risk and improvement scores, and can be varied to reflect differing scenarios.

4. AI applications case studies

In the next sub-sections, the various case studies for AI applications in the energy sector shown in Fig. 5 will be described in order to understand the classification process with the 3D indicator. The case studies have been ordered in the sub-sections following the AI taxonomy described in Fig. 1, and a brief description of each AI subgroup is given. Table 1 summarises the classification results used to create the visual representation. Although this selection is a partial overview of the field, it offers a small insight into the current challenges and a first assessment of the developed indicator tool for energy applications. Results of the classification and ranking procedure are given in Section 5, and the discussion and outcomes can be found in Section 6.

4.1. Machine learning

ML is usually split into three subsets: Supervised, Reinforcement and Unsupervised Learning. They all aim to create systems which learn new features from input data, but the way in which they learn is different, and therefore they solve different problems.

Supervised Learning (SL)

In a nutshell, SL consists in learning based on example input–output pairs. In the energy field, this is mainly used for forecasting and predictive maintenance. For example, *forecasting methods* such as weather forecasts are particularly useful for renewable energy planning, and novel data-driven models are being developed to compete with existing operational forecasts. The accuracy levels of these new methods do not always warrant the replacement of physical modelling [47], but the use of AI allows for significant gains in computational efficiency, which makes it particularly promising [48–50]. AI forecasting solutions are already widely implemented in the industry, and are therefore at the highest maturity level (TRL 9), as they are being extensively applied in wind farms [51] or for solar irradiance forecasting [56]. They present a limited risk level as they generate content which will then be used to inform human decisions, and have the potential to save computational time, and therefore economical investment, as well as to make energy more valuable to the grid as it enables previously unpredictable energy sources to become scheduled [51].

Another example is *energy consumption optimisation* solutions [59, 60], such as Google's DeepMind project [57], where they have experimented in data centres with an intelligent control framework to optimise the energy consumption of cooling. Based on historical data collected by thousands of sensors, they trained a set of deep neural networks to improve data centre energy efficiency. This application allows them to consistently reduce energy consumption for cooling by 40% and to save time since engineering custom-tuned models may not be duplicated. This AI model is not yet widespread in all data centres, but it has gone beyond the demonstration stage to be implemented into several industrial sites (TRL 6) [58]. The level of risk is considered high due to the direct link with critical infrastructure, although risks can be limited through human supervision in the same way as more traditional engineering methods.

Predictive maintenance is a widespread use case of SL, and a research team from CSEM has developed a method to predict, and therefore avoid, failures that may occur on wind turbines [61]. This tool has been applied to nearly 200 turbines and has prevented some 40 failures over one year. Such a tool provides improvement for all the three aspects evaluated; energy, time and finances. Moreover, industry applications of such AI applications already exist on the market [62–64], placing it on TRL 8, with high risk as it affects the safety of power systems.

Finally, *fraud/churn detection* is an example of an AI application with unacceptable risk under the EU AI Act proposal, as it utilises SL predictive modelling to identify zones of fraud or market churn for utility companies, based on social and economic parameters from customer data [65–67]. For fraud detection, the main goal is to avoid non-technical losses by targeting geographic zones where meter tampering or irregularities in the grid are detected through the AI application, essentially creating social profiling and geographic zoning. In the case of churn detection, the AI application is designed to predict when customers are likely to change utility company in liberalised markets, in order to provide them with new incentives and offers to increase customer retention.

Reinforcement Learning (RL)

RL is a decision-making method via interaction and feedback. In other words, this is a set of techniques aimed at solving complex sequential decision-making problems. The ability of these algorithms to make optimal decisions at each time step makes them well suited to control problems.

For example, typical use case are the *control of a battery in a micro-grid* [68,70–72] or the *optimal charging of electric vehicles (EV)* [74,75]. There is some interest in automating these processes, although the energy and economical gain is currently limited. In the long-term, the objective will be to control efficiently and in real time more complex systems which today require significant computing time. Both these use cases are high risk AI applications within the EC framework, as they deal with power infrastructures and consumer access to resources. Their TRL is between 3 and 4, as experimental pilots exist but remain small scale [69,73,76].

Another well-suited use case of RL methods is *trading in the electricity market*. Trading problems are highly stochastic and require making a decision at each time step. In the literature, different applications for trading already exist and are starting to be applicable to the electricity market [80,81]. Due to the amount of money involved and the associated security of supply, the level of risk and caution required are high, as algorithm bias or prediction errors could lead to negative socioeconomic impacts. Such uses of AI are already widespread in the trading market [82–84], resulting in a TRL level 8, allowing traders to save time and finances. Moreover, electricity trading in microgrids or small scale residential areas [85] could lead to energy efficiency gains, as the energy can be used directly in the neighbourhood instead of being fed into the grid, where losses can occur.

Unsupervised Learning (UL)

UL is about data representation, and more specifically about extracting underlying structure in data. For examples, this technique can be used to construct representations to improve a supervised or RL system, create clusters for unlabelled data, or serve as a tool for anomaly detection [89,118–120]. One of the most popular methods of unsupervised learning is k-means clustering. The goal of this algorithm is to find K groups in the data, essentially classifying data sets autonomously.

This method is used in a wide range of applications and, for example, fits well with *clustering consumption patterns*. Among other things, it allows the tens of thousands of household energy consumption values to be transformed into a few representative daily profiles. The characteristics of these typical days can then be analysed much more easily in order to identify potential measures for reducing energy costs [87]. As a generalisation of this clustering practice, *pattern discovery* involves generalising data analysis, potentially on a spatial scale, at different levels of aggregation to derive new information and auto-correlation relationships. Another application may be to automatically *assess consumer flexibility* through analysis of their load curve [92,93]. While these energy applications have attracted research interest, their implementation at industrial levels remains weak, and the associated risk is high due to the potential direct impact on people's electricity mix. This risk is limited for *pattern discovery* if the application only handles data to extract insights, which falls under the category of content generation, which is why this application already sees a few use cases (TRL 7) in the Swiss Federal Administration [96] or at ENTSO-E [97]. Moreover, although these solutions can yield energy and economical gains, current case study examples show low added value, and lack of business models may partly explain the low market interest [90,91].

Finally, *policy analysis* is a good representative use case that combines all three subsets of ML. This application aims at analysing data to identify useful patterns and support decision making. The domains of application in the energy sector are varied but the associated risk remains high due to the impact on human interests, network planning and energy policy design. *Policy analysis* is an important concept in public administration notably, which has encouraged several pilot projects (TRL 6) to better analyse different situations in order to potentially save time, energy and finances.

4.2. Planning

Planning is a subset of AI which solves planning and scheduling problems [121]. This method defines, step by step, the actions to be taken to reach an end state from a starting point. Its field of application is similar to RL, except that the model of the environment is assumed to be known. The most popular use cases of AI planning come with typical challenges in business, such as vehicle routing problems, maintenance scheduling, employee rostering and task assignment. Most of the use cases in the energy field are related to RL applications.

4.3. Computer Vision (CV)

Computer vision enables computers and systems to derive meaningful information from visual inputs, and take actions or make recommendations based on that information. This technology is mainly based on convolutional neural networks (CNN). A CNN breaks images down into pixels that are given tags or labels. It then uses these labels to perform convolutions, which essentially is a mathematical function used to extract features from the original image. Computer vision has many applications in industry, such as image classification, object tracking or automated fault detection.

In the energy sector, this technology is already used for industrial applications, specifically in the field of *geospatial image analysis*. A first example is the Swiss company Pictera [102] – their main services consist in monitoring infrastructures using satellite imagery and CV, such as railroads for the SBB (Swiss Federal Railways) and power lines, to detect and prevent possible failures. Another industrial use case is the project Sunroof from Google [103]. This algorithm computes the solar potential of rooftops based on satellite imagery and historical weather data. This product saves time in evaluating the solar potential in cities and is available since 2015 in the United States and since 2017 in France [104]. Being at the heart of existing company's business models, these AI technologies have a high level of maturity (TRL 8).

Another use case for CV is *production line fault detection*, for example in the PV industry with electroluminescence or thermal imagery analysis to automatically identify faults based on CNN classification [105,107]. These applications are widely used in industry (TRL 9), but still have improvement margins to further increase production line efficiencies.

For all the covered CV use cases, risk levels are limited as these application mainly create content and outputs that require additional human inputs and validation, although some fault detection applications could warrant a high risk level if applied without supervision, as they deal with the safety of critical infrastructure.

4.4. Robotics (RB)

The boom in big data, cloud computing and AI has also pushed industrial and academic researchers to focus on robotics [122,123]. The idea behind AI robotics is to further enhance the efficiency and intelligence of robots in the field of design, development and production. Energy companies used robots for safety, inspection, and maintenance purposes.

As an example of a use case, a group of researchers at the University of British Columbia in Canada created an *AI-driven robot* that searches automatically for new solar cell film designs [108]. The robot can synthesise new materials and evaluate their conductivity and microstructures autonomously, with an optimisation algorithm choosing the next research steps. This allowed the research process to be sped-up exponentially. Another example is the use of AI robots in the offshore wind industry, where it is envisioned that intelligent robotics will play a vital role in the infrastructure life cycle, from planning, design, maintenance and decommissioning [109]. Although these types of applications are not yet widespread (TRL 5 with demonstration pilot), they have the potential to save considerable time with limited to high risk, depending on the target infrastructure.

On the same note, some companies like Aerialtronics [111] or Hepta Airbone [112], design and build *AI powered drones*. These can then be used for autonomous, real-time fault detection, for instance in wind turbines or power lines [113]. They can detect structural defects, electrical malfunctions, assembly errors and vegetation overgrowth. Drones are also widely used for autonomous fault detection in larger-scale PV plants [116,117]. The AI application potential on the three-dimensional indicator is similar to computer vision, with a greater notion of risk due to the security of supply associated with the infrastructure.

5. Results of the AI application classification and ranking

Fig. 5 shows the resulting AI application classification using the proposed 3D indicator, where each application is visually represented within the three dimensions of risk, maturity and improvement. This simple representation condenses all the information of Table 1 in an informative way for policy makers, researchers and industry, and enables a quick status comparison of the main AI applications in the energy sector.

Following the categorisation of AI applications, it is also interesting to create a ranking system taking into consideration all three dimensions of the proposed indicator. As described in Section 3 and following Eq. (1), three weighting scenarios are considered:

- *Balanced*: this represents the baseline scenarios, where each dimension is considered equally ($\omega_1 = 0.33$, $\omega_2 = 0.33$, $\omega_3 = 0.33$).
- *Profit-seeking*: this scenario assumes higher importance on the TRL scale, reflecting industry and business interest in AI applications with proven track records to bring added value ($\omega_1 = 0.80$, $\omega_2 = 0.10$, $\omega_3 = 0.10$).
- *Risk-avoidance*: this scenario focuses on the policy maker interest of keeping AI applications within the regulatory framework guidelines and minimising risks, with higher importance on the risk scale ($\omega_1 = 0.10$, $\omega_2 = 0.80$, $\omega_3 = 0.10$).

Fig. 6 shows the results for all three scenarios in the form of a bar and radar chart. The bar chart allows one to compare the AI application score D and order the applications from best to worst, where a lower value of D is best as it represents the weighted distance from optimum indicator scores. The radar chart is built using $1 - D$, such that a higher score indicates better performance.

The next section will provide a discussion of the main insights and outcomes of the novel three-dimensional indicator and ranking.

6. Discussion and outcomes

This study presents a novel multidimensional indicator for guiding AI use in energy applications, based on three key metrics: maturity, risk, and improvement. The purpose of such an indicator is twofold: to facilitate the comparison of AI applications and to identify future prospects for any AI project, from a research, industry, and policy perspective.

In the previous subsections, this indicator has been applied to multiple case studies related to energy systems. The proposed classification, presented in Table 1 and Fig. 5, is an illustrative showcase of the developed indicator — ideally, support from legal experts and in-depth risk assessments would be advised for future iterations of this procedure. The summary of these results provides a short overview of AI developments in the field. Indeed, by comparing on a common basis the reviewed use cases, regardless of their AI subgroup, the indicator allows for a better characterisation of current AI uses and their standing with regards to the newly proposed EU AI Act and industry implementation, giving an overall picture of the status of AI use in the sector.

The first key parameter of the novel indicator, the maturity level, is the least debatable criterion as it is directly linked to the penetration of the project in industrial activities. A first conclusion which can be drawn is the spread of applications in terms of maturity. Although AI technology emergence is relatively recent, and particularly the development of connected devices, as shown in Fig. 2, AI is already at the core of several companies' business model. Indeed, among the AI applications analysed, a majority are at the implementation stage in industry. This demonstrates a rapid market integration for some of these applications. Looking at Fig. 5, AI applications with a TRL above 4 seem to share two common characteristics. On the one hand, their risk level is limited for the higher TRL scores, which could be an indication of the importance of safety and increased human supervision needed for

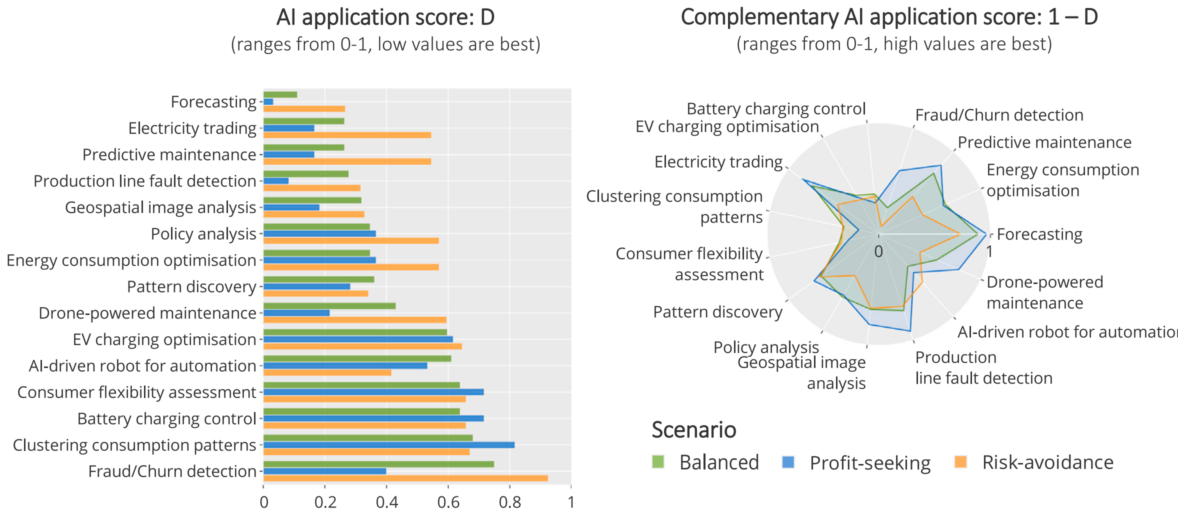

Fig. 6. Results of the AI application score ranking. Left: Comparison of the AI application score D for the three scenarios, ordered from best to worst performing AI application for the Balanced scenario (top to bottom), where a lower value of D is best as it represents the weighted distance from optimum indicator scores. Right: Radar chart comparison of $1 - D$ for the three scenarios, where a higher score indicates better performance.

high risk applications to reach full market penetration. On the other hand, time savings seem to be a key element, followed in decreasing order of priority by economical and energy savings, highlighting the need for efficiency gains in processes and computing time.

The level of risk is assessed according to criteria that are intended to be objective, taking into account the comparison with current solutions, security of supply and compliance with existing legislation on fundamental rights. This provides a second key outcome of the developed indicator, which is the large number of AI solutions classified in the high risk level. This is mainly due to the fact that the energy and power sectors are considered key infrastructures, and therefore fall within the high risk category in the EC AI Act when dealing with safety components of the grid. If the proposal were to be ratified and put into effect, the concrete impact on these technologies would be a more stringent development process. The EU AI Act proposal outlines the additional steps needed for such high risk AI applications [14]: these technologies must (i) be developed with impact assessments and follow codes of conduct, (ii) undergo conformity assessments and comply with AI requirements set by the EU AI Act during its life cycle, (iii) be registered in a dedicated EU database, (iv) sign a declaration of conformity and carry the CE marking (Conformité Européenne). Moreover, even after market approval, authorities on Union and Member State level will be responsible for market surveillance, monitoring and human oversight, while providers have a post-market monitoring system in place. Providers and users should also report incidents and malfunctions, and there are transparency obligations (disclosure) for providers to notify the use of AI applications to users. In other words, this notion of high risk associated with key infrastructures, such as energy systems, may slow down the maturity transition for some applications, but ensure a better control of the ones deployed in the market.

Finally, the degree of improvement aims at assessing the technological gain compared to current solutions, and is established through case study results and simulated enhancements. This criterion leverages on real comparative assessments of the AI application with previous methods or case study reports of these AI solutions. Scoring the improvement at three levels allows for a common evaluation of applications with distinct objectives. The three categories chosen (i.e., energy, time, finance) were selected to best meet the objectives of the projects in the energy field, but other categories could easily be added or considered. An exact quantification of the improvement potential is not straight-forward, as most of the AI applications do not impact the same resources and are therefore not directly comparable. This is why the three-level scale is chosen, as it can simply and effectively reflect the versatility of the gains. At a glance, a policy maker or industry partner can therefore identify AI applications which can save energy, time and/or investments. Within each application, more robust comparisons and improvement metrics can then be used as a next step in the analysis process. The results from Table 1 and Fig. 5 show that most applications achieve savings on two or even three levels. This is a natural finding, as these three parameters are often linked. Nevertheless, time savings seem to be a key feature of AI applications, especially those of medium and high maturity.

More generally, the quadrants of the proposed visualisation shown in Fig. 5 also provide interesting insights on the positioning of AI application within the indicator landscape. The ideal location for a given AI application is Q1, with minimal risk and high TRL. Quadrant Q2 is the unacceptable zone, where applications should never end up in as they would be at high industry penetration levels whilst sustaining severe ethical, security or societal risks. Applications within Q3 that have high improvement potential will likely move rapidly towards higher maturity levels. Finally, Q4 applications should be avoided, however they could exist at research level as long as they prioritise lowering their risk level if higher TRL scores are to be reached.

In addition to the visualisation of AI applications within the 3D indicator space, a ranking framework is proposed based on the distance from the optimal value for each indicator, with varying weights associated to each dimension. Fig. 6 shows the results for the three considered scenarios. From this ranking, one can conclude that the most promising AI applications for the balanced scenario are the following: forecasting, electricity trading, predictive maintenance and production line fault detection, as they have the lowest AI application score D. The sensitivity analysis shows that the profit-seeking scenario, which puts higher emphasis on the TRL, stays similar to the balanced scenario, with few changes in the top ranked AI applications. However, the risk-avoidance scenario, which places higher importance on low risk applications, sees forecasting, production line fault detection and geospatial image analysis as top ranking applications, as they show high savings potentials with limited associated risk. Alternative scenarios and weighting schemes would lead to different results, for example focusing on solutions in the research stage with high savings potential, highlighting how this indicator framework can be used to extract meaningful insights for industry, policy makers and research.

Overall, the proposed indicator shows that (i) AI applications in the energy sector are already highly advanced in terms of market penetration, with many promising solutions for the energy transition already at industry deployment level, (ii) a majority of applications are categorised as high risk within the EC framework, which would entail additional steps in the development process of new technologies, (iii) most AI solutions lead to economical and energy savings, and a more robust quantification of these savings can be done for each AI application individually, (iv) applying a simple ranking with sensitivity analysis can yield useful outcomes and guide the integration and implementation of AI applications with the highest potential, whether it be in terms of maturity, risk or improvement.

7. Conclusion and outlook

The decarbonisation of the energy sector is evolving at unprecedented rates, lead by climate policy efforts which also raise the need for efficient use of energy system assets while integrating a large amount of novel, increasingly digital technologies. There already exist a multitude of AI applications with promising potential to support the transition towards decarbonised energy systems, and this paper aims at creating a novel three-dimensional indicator to classify them within a simple and insightful framework. The proposed approach can help different stakeholders to rank available AI applications in terms of regulatory risk, potential societal improvements and economic benefits. For example, the indicator and its accompanying visualisations can be used as decision support for policy makers to design new policies around AI, for investors and businesses to follow and rank technology trends, or for public research agencies to prioritise and allocate funding to bring promising AI applications to maturity.

The main findings of this work can be summarised as follows:

- The proposed three-dimensional indicator highlights the current potential of AI applications for the energy sector in an informative way.
- The multidimensional indicator allows stakeholders to assess the benefits for a given AI application from different angles, incorporated through weighting schemes.
- The proposed review of AI applications shows that many solutions in the energy sector are already at deployment level, with a majority categorised as high risk due to the direct link with critical infrastructure.
- The ranking scenarios based on the indicator score metric showed that the most interesting applications overall are forecasting, predictive maintenance, electricity trading, drone-powered maintenance and geospatial image analysis, with forecasting applications also coming on top in the risk-avoidance scenario where the risk level is emphasised.
- Expanding the indicator with additional dimensions could lead to further interesting insights, e.g. incorporating a quantification of improvement potentials, or looking at carbon savings, security of supply, system reliability, etc.
- The methodology can easily be generalised to other AI applications and sectors or incorporate new AI applications.

CRediT authorship contribution statement

Hugo Quest: Conceptualisation, Formal analysis, Investigation, Methodology, Visualisation, Writing – original draft. **Marine Cauz:** Conceptualisation, Formal analysis, Investigation, Methodology, Writing – original draft. **Fabian Heymann:** Formal analysis, Investigation, Writing – review & editing, Supervision. **Christian Rod:** Writing – review & editing, Supervision. **Lionel Perret:** Writing – review & editing, Supervision. **Christophe Ballif:** Writing – review & editing, Supervision. **Alessandro Virtuani:** Writing – review & editing, Supervision. **Nicolas Wyrsch:** Conceptualisation, Validation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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