Position paper

An analysis of the implementation of artificial intelligence in the energy sector

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The European Energy Research Alliance (EERA) is the association of European public research centres and universities active in low-carbon energy research. EERA pursues the mission of catalysing European energy research for a climate-neutral society by 2050. Bringing together more than 250 organisations from over 30 countries, EERA is Europe's largest energy research community. EERA coordinates its research activities through 18 Joint Programmes and is a key player in the European Union's Strategic Energy Technology (SET) Plan.

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Foreword

At the time of writing this preface, the dislocation of the Post WW II World Order towards an emerging World Dis-Order, is happening as we speak. The Rule of Power almost instantly replaced the pre-existing Rule of Law in an unprecedented reshuffling of historical alliances, capturing the entire world political attention and largely eclipsing the existential emergency of collectively addressing climate change.

Despite this highly regrettable juncture, the need to accelerate the EU clean energy transition is more than ever critical in times where fossil energy supply is increasingly weaponised and EU's strategic autonomy more than ever challenged.

Shifting our legacy fossil fuel-based economy towards a low-carbon driven one is indeed the only strategy ensuring a high level of energy sovereignty, i.e. guaranteeing a reliable and cheap energy supply, shielded from imported fossil fuel market spikes and geopolitical manipulations.

At the same time, even in countries highly committed to advancing the energy transition, it is becoming obvious that the deep decarbonisation of the economy is more challenging than initially thought, requiring a fundamental shift in the ways we produce, store, distribute and use energy.

Such a transition will require accelerated innovation to occur both from technology and societal perspectives, that will rely on a profound understanding of complex systems. Through its recent breathtaking advances, Artificial Intelligence (AI), with its capacity for data analysis, pattern recognition, and predictive modelling emerge as an essential enabler of this unprecedented dual technology and societal transformation.

It provides a timely strategic perspective on how AI could best be used to accelerate the energy transition, delving deeply into specific applications, challenges, and future directions. It offers a holistic perspective enriching our understanding of both the immense potential and the inherent complexities of integrating AI into the energy sector design and operations.

In particular, it examines how the various AI techniques – from machine learning and deep learning to digital twins and expert systems –can optimise energy production (renewable energy forecasting, smart grids, predictive maintenance), enhance efficiency (building energy management, demand response), and improve the overall sustainability of energy systems.

The White Paper also discusses the critical challenges associated with the use of AI, including its resources footprint as well as ethical and trustworthiness considerations relating to its use in safety critical infrastructures, such as transparency, data quality, and model explainability, all highlighting the importance of establishing stringent ethical guidelines and a strong regulatory framework.

Recognising that the energy transition, beyond a shift from traditional fossil fuel based technologies to low carbon ones, also requires a deep societal transformation, the White Paper emphasises how AI can help adopting a human-centric approach, showcasing through a number of real-world applications and case studies, how it can be used, notably to tailor energy solutions to individual needs, promote efficient consumption, and enhance the overall trust and acceptance of new technologies.

The present White Paper constitutes an invaluable resource for researchers, policymakers, industry professionals, and other AI stakeholders, providing a comprehensive overview of AI's transformative potential in shaping a sustainable energy future. It demonstrates and showcases the multiplicity of AI applications enabling an accelerated understanding, planning and implementation of the energy transition while highlighting its intrinsic challenges calling for an indispensable and well-designed strong regulatory framework guaranteeing it actually delivers within stringent resources and ethical constraints.

Finally, the present paper should be considered as a timely, though time stamped contribution, for better assessing AI technologies, of which the speed of development and high unpredictability call for modesty and continuous re-assessment.

Adel El Gammal
EERA Secretary General

Executive summary

Artificial Intelligence (AI) is playing an increasingly important role in the energy sector, offering transformative benefits across multiple facets of energy production, distribution, consumption, and management. Several key ways in which AI is being used and its importance are:

- Optimisation of Energy Production and Distribution
  - Grid Management: AI can optimise the operation of electrical grids by predicting demand and generation, providing recommendations in real-time to solve technical problems (e.g., grid congestions, under/over-voltage), and predicting outages. Advanced algorithms help balance supply and demand in real time, reduce energy loss, and improve grids' reliability.
  - Renewable Energy Integration: AI can help manage the variability and uncertainty of renewable energy sources, such as wind and solar. Machine learning algorithms forecast weather conditions and energy production from renewables, enabling more efficient integration into the grid and reducing reliance on fossil fuels.
  - Energy Storage Management: AI optimises the use of energy storage systems by predicting the best times to charge and discharge batteries, reducing energy costs and ensuring a steady supply.
- Energy Efficiency and Consumption
  - Smart Meters and Smart Homes: AI-powered smart meters and home automation systems monitor and control energy usage in real time, enabling consumers to optimise their energy consumption, reduce waste, and lower costs.
  - Building Energy Management: AI systems can control heating, cooling, and lighting in buildings based on occupancy and weather forecasts, reducing energy waste and improving efficiency.
  - Demand Response: AI can manage demand-response programmes, which incentivise consumers to reduce their energy use during peak demand periods, lowering overall consumption and minimising stress on the grid.
- Predictive Maintenance
  - Asset Management: AI can predict when power plants, turbines, and other energy assets are likely to fail (and explain the causes), allowing for proactive maintenance and reducing downtime, while increasing safety. This leads to cost savings and increased asset life.
  - Fault Detection and Diagnostics: AI can detect anomalies in energy systems, such as grid faults or equipment malfunctions, and quickly diagnose the issues, minimising operational disruptions.
- Advanced Data Analytics and Forecasting
  - Energy Demand Forecasting: AI can analyse historical data, weather patterns, and socio-economic trends to predict energy demand more accurately. This helps energy providers plan better for future needs and optimise their operations.
  - Price Forecasting: AI can forecast energy prices by analysing market conditions, geopolitical events, and supply-demand imbalances, helping businesses and consumers make more informed decisions about when to buy or use energy.
- Sustainability and Carbon Emissions Reduction
  - Carbon Footprint Monitoring: AI can track and analyse carbon emissions across the energy supply chain, helping companies meet sustainability goals and comply with regulations.

  - Renewable Energy Forecasting: AI can predict renewable energy output (like solar and wind), enabling better planning and minimising the use of fossil fuels when renewable energy is low.
  - Optimisation of Fuel Usage: AI models help optimise the use of fossil fuels in power generation by adjusting operations to reduce emissions while maintaining reliability.
- Energy Trading and Market Efficiency
  - Automated Energy Trading: AI algorithms are used in energy markets to predict price movements and make high-frequency trading decisions. This helps market participants, such as utilities and financial firms, optimise their energy purchasing strategies.
  - Supply Chain Optimisation: AI can optimise the entire energy supply chain, from raw material extraction (e.g., coal, natural gas) to delivery and consumption, improving efficiency and reducing costs.
- Decentralisation and Smart Grids
  - Decentralised Energy Systems: AI supports the development of decentralised energy systems, where consumers (e.g., with rooftop solar or small wind turbines) can both generate and consume energy. AI helps to manage the flow of energy in and out of these systems, allowing for better integration into the larger grid.
  - Blockchain and AI Integration: AI, combined with blockchain, is being explored to create decentralised energy trading platforms, where consumers can directly trade energy with each other, reducing transaction costs and improving market efficiency.
- Electric Vehicles (EVs) and Charging Infrastructure
  - EV Charging Optimisation: AI optimises the charging of EVs, predicting when to charge based on grid conditions and user preferences, ensuring an efficient, cost-effective system.
  - EV Fleet Management: AI is used to manage fleets of EVs, ensuring that they are charged and maintained properly, and coordinating their use to minimise downtime.

AI's importance in the energy sector lies in its ability to drive efficiencies, improve decision-making, reduce environmental impact, and enable the transition to a more sustainable energy future. By improving energy management, predicting trends, optimising infrastructure, and enabling smarter consumer behaviour, AI is key to the modernisation of the global energy landscape.

In this position paper, EERA analyses not only the current state-of-the-art and specific use cases and success stories in which AI is driving new advances in the energy sector but also the technology perspective that will guide the future, both for the research and production domains.

Lateral outcomes that AI is producing are studied in terms of the potential pitfalls and limitations that show up when using AI, the trustworthiness that must be achieved, the human-centric approach for property harnessing AI in social research, including the benefits for the energy sector, and the energy consumption and CO2 emissions that AI produces in large data centres.

Finally, some conclusions and future steps are described.

By the way, most of this executive summary has been written by generative AI - demonstrating its potential in helping humans structuring and presenting relevant information.

Introduction

The European Commission defines Artificial Intelligence (AI) as software systems created by people that, when faced with a complex objective, operate in the physical or digital realm by perceiving their environment, acquiring and interpreting structured or unstructured data, reasoning on the knowledge, processing that information, and deciding on the best actions to achieve their goal.

AI is a key component of the fourth industrial revolution, and as in other sectors, it is already being applied in the energy industry. But how can it help meet Europe's decarbonisation goals? Its role will be crucial in achieving a more sustainable future as we are now in a period where energy systems are becoming increasingly complex as demand grows and decarbonisation efforts intensify.

Yet a clean, modern and decarbonised grid will be vital in the broader move to a net-zero emissions economy. Some steps beyond are data centre operators exploring alternative power options, like nuclear technologies, to power sites or storage technologies such as hydrogen. Also, companies' investments in emerging tech such as carbon removal, to remove CO_2 from the air and store it safely.

As in the previous cases, AI can also play a role in overcoming barriers to integrating the necessary vast amounts of renewable energy into existing grids. For example, the variability in renewable energy production often results in overproduction during peak times and underproduction during lulls, leading to wasteful energy consumption and grid instability. By analysing vast datasets, from weather patterns to energy consumption trends, AI can forecast energy production with remarkable accuracy. Moreover, AI helps to simplify processes aimed at improving energy efficiency and facilitating the transition to renewable energy.

For the sake of awareness, Elsevier has launched the 'Energy and AI' journal. Focal points of the journal include but are not limited to: automation of science discovery related to energy materials and chemistry; digital twinning or big data analytics of complex energy processes/systems; data-driven design of energy materials, devices and systems; internet-of-things and cyber-physical energy systems; AI for human factors in energy-related activities; virtual reality applied to energy and environment; autonomous systems for energy efficiency maximisation; hardware for data collections in energy systems; data science for energy applications; hybrid data-driven and physical modelling for energy-related problems; intelligent control of energy systems; AI, energy and society; AI safety, reliability and ethics within energy applications; AI for life-cycle assessment or energy and decarbonisation roadmaps; or, energy robotics.

So it is clear that AI will play a cornerstone role in achieving a clean energy transition thanks to the huge amount of available data, but there are also some drawbacks that should be taken into account. In this data-rich field, there is a growing need for enhanced information sharing and more powerful tools, such as those offered by AI, to plan and operate evolving energy systems. This need arises just as AI capabilities are advancing rapidly. Since 2010, as machine learning models have become more sophisticated, the computational power required to develop them has doubled approximately every five to six months.

On the other hand, the use of supercomputers to develop AI capabilities is an energy consumption and CO_2 producer *per se* as it represents 1.5% of the yearly world electricity consumption according to the IEA (this percentage increases to 6% if we account for ICT as a whole). Thus, Microsoft, which has invested in ChatGPT maker OpenAI and has positioned generative AI tools at the heart of its product offering, recently announced its CO_2 emissions had risen nearly 30% since 2020 due to data centre expansion. Google's GHG emissions in 2023 were almost 50% higher than in 2019, largely due to the energy demand tied to data centres. So a question arises, do the benefits that AI brings to help reducing CO2 emissions outweigh the increased energy consumption and CO2 emissions it requires and causes?

Even more, are we properly accounting the energy consumption that the world produces as "simple" users of generative AI tools such as ChatGPT, Copilot, Gemini, etc.? In this scenario, will the recent launching of DeepSeek (Deepseek-AI et al. 2024) change this trend dramatically as it claims that only one tenth of the electric power is required for providing similar results so the building of those huge data centres will become obsolete?

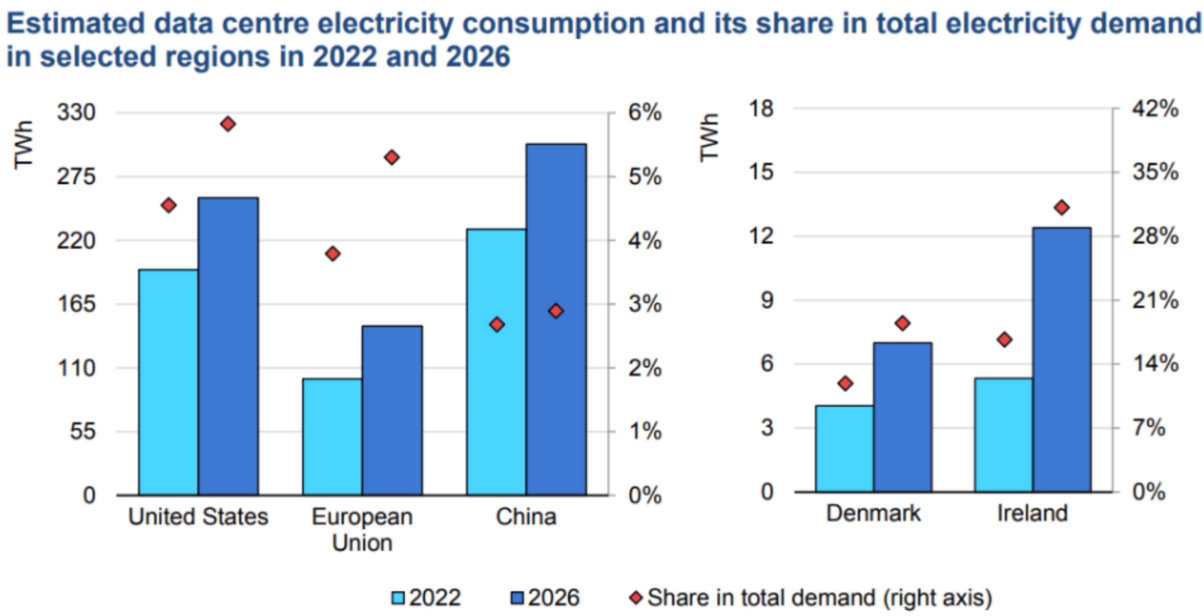

Fig. 1. Data centre electricity consumption around the world. Source: IEA, Electricity 2024. CC BY 4.0.

Last but not least, regulators including the European Parliament are beginning to establish requirements for systems to be designed with the capability of logging their energy consumption. Under this wider scenario, AI will necessarily be the pillar of extracting useful information from this amount of data that will result in an effective clean energy transition.

In this paper, EERA analyses how AI is affecting the energy research domain and what trends are pushing the coming years, taking into account the associated drawbacks.

AI state-of-the-art and trends

AI is a clear advantage, anyway. For example, AI, along with the use of robots and drones, enables faster, safer, and more efficient operations and inspections in the environments where infrastructures are located. Moreover, innovative technologies such as AI, Building Information Modelling (BIM), and digital twins make the operation of infrastructures significantly more efficient. Digital twins are also very useful for creating simulations of infrastructures, allowing for performance optimisation through detailed scenarios and analyses in virtual environments.

AI algorithms can also very accurately predict the likelihood of incidents occurring in installations, making it easier to implement preventive measures before problems arise. In the event of a failure, AI analyses the causes, severity, and potential consequences, quickly determining the necessary actions to be taken. This improves safety and reliability while also reducing maintenance costs.

AI cannot store and transport energy, that is true, but it is indeed useful for optimising operations and improving decision-making processes. For instance, AI algorithms are used to predict gas demand and consequently adjust transportation and storage operations. Additionally, AI helps to identify patterns in energy consumption that can lead to opportunities for implementing more sustainable practices.

In other domains, such as the production and supply of various energy products, the application of AI is already a reality. This is based on a fully connected Industry 4.0, with real-time data processing capabilities, which allows for maximising production and distribution capacity, and continually improving efficiency.

Closer to the research activity, AI algorithms analyse data from renewable energy sources such as solar panels and wind turbines, predict energy generation, adjust demand, and improve system performance. By incorporating factors such as weather patterns and historical data, AI delivers more accurate forecasts, ensuring the efficient utilisation of renewable resources.

In use cases with challenging requirements in terms of computational time (e.g., solving an optimisation problem with a state-of-the-art solver takes minutes or hours), imitation (supervised) learning and reinforcement learning (RL) are emerging as potential solutions due to the very fast inference time of AI models, such as artificial neural networks. Imitation learning requires a model-driven "expert" that generates demonstrations that a second data-driven model attempts to replicate/learn. In contrast, RL involves learning optimal policies through interaction with an environment. Instead of relying on pre-labelled data, the model explores "autonomously" different actions and learns from the consequences of those actions. Success cases like AlphaGo Zero AI (Silver et al., 2017) showed training capability (i.e., capacity to discover new knowledge from scratch) with improved convergence of RL without human examples/guidance or domain knowledge. Yet, one of the key outcomes of research on GPT-3 language models was the development of RL from human feedback. In this process, human-submitted prompts are used to fine-tune GPT-3 (Christiano et al., 2017). The AI creates a model to identify the reward function that best reflects human judgments. Developments in 'planning' with Monte Carlo tree search that dynamically visits and simulates the future state for narrowing down the search space (Silver et al., 2017), or 'imagination' where AI agents can build the capability to 'imagine' and reason about the future and construct a plan using this knowledge (Racanière et al., 2017), can significantly enhance RL-based agents' predictive capabilities. These advancements are particularly relevant for various use cases in the energy sector, offering improved forecasting and decision-making. Scalability remains a major challenge in the field of RL. Research in distributed and hierarchical RL offers promising solutions to this issue, paving the way for broader industrial applications (Mussi et al., 2024).

Knowledge representation is also a key aspect of the success of data-driven approaches. Graph-based representation, particularly graph neural networks or knowledge graphs, are emerging as very efficient knowledge models (Dong et al., 2020) for large-scale structured data in complex domains such as electrical networks. Also, in terms of knowledge representation, large language models (LLM) are going beyond textual data. Foundation models pre-trained on a broad spectrum of generalised and unlabelled data can be applied to different general tasks (i.e., zero-shot learning), such as time series forecasting (Das et al., 2023) or dynamic system simulation (Seifner et al., 2024).

Another trend is the hybridisation between AI and other disciplines, particularly physics and operations research. One notable example is physics-informed machine learning, which integrates physical laws and constraints into ML models to improve their accuracy and generalisation. It can also accelerate the simulation capabilities of traditional simulation techniques and software (Karniadakis et al., 2021). Another remarkable development is the combination of ML with mathematical optimisation, exploring several possibilities such as the fast approximate prediction of solutions to combinatorial optimisation problems and the combination of data-driven inference with combinatorial optimisation solvers for structured logical reasoning (Kotary et al., 2021), or the use of implicit layers to directly enforce constraints within neural networks (Amos and Kolter, 2017).

In addition, AI is increasingly being integrated into the field of safety and reliability, particularly through the application of Machine Learning (ML). ML methods have demonstrated strong capabilities in processing complex data, identifying patterns, and making predictions in various domains of industrial safety and reliability. These applications include fault detection and diagnosis, anomaly detection, system prognosis, reliability analysis, and risk assessment (Tamascelli et al., 2024). ML techniques, particularly supervised learning, have been widely adopted, offering practical solutions to manage safety risks and enhance system reliability. However, the implementation of ML in these areas is still in its early stages, characterised by significant potential for future exploration and development (Xu and Saleh, 2021; Nassif et al., 2021).

Supervised learning remains the most dominant ML technique in safety-related applications, particularly in fault detection and diagnosis, which rely on classification methods to identify and categorise system anomalies. However, recent studies indicate a growing interest in semi-supervised and unsupervised approaches, which are proving effective in anomaly detection and risk assessment, where labelled data are often scarce. Unsupervised clustering algorithms have been successfully applied to detect anomalies in complex systems, while dimensionality reduction techniques further enhance the efficiency of these models by simplifying high-dimensional data (Fuertes et al., 2016; Sunal et al., 2022).

Despite significant progress, challenges remain in applying ML to safety and reliability. Data scarcity, particularly the lack of labelled and real-world industrial data, poses substantial obstacles to ML model development. Most research relies on experimental or simulated data, which may not fully capture the complexities of actual operating conditions. Moreover, data quality, trust, and explainability issues are central to the ongoing integration of ML in safety-critical environments. Interdisciplinary collaboration between data scientists and safety experts is crucial to address these challenges and foster the development of more interpretable and reliable ML models for industrial safety applications (Paltrinieri et al., 2019; Tamascelli et al., 2023).

AI and energy: some examples

There is a plethora of use cases in which AI has been applied to the energy sector. The reader can consult (Hoffmann et al. 2022, Wang et al. 2024), for example. In this section, some fields will be analysed to illustrate the impact of AI on them and how it is pushing efficiency in the energy sector.

Nuclear materials

AI and especially ML are increasingly integrated into energy materials science to accelerate materials discovery (entirely new materials) and development (composition and/or architecture tuning to target use for a specific application, or simply to improve specific properties, within a known class of materials), in so-called materials acceleration platforms (MAPs) (Flores-Leonar et al., 2020; Wagner et al., 2021). They are equally used to optimise fabrication and manufacturing processes (Ciccone et al., 2023), as well as to enhance the reliability or the reach of methodologies applied to the prediction of material performance and property degradation in operation (Gupta et al., 2023; Ferreño et al., 2021). Finally, they are entering the field of materials health monitoring in operation (Azad et al., 2023), by enabling the fast analysis of thousands of data coming from sensors applied to materials and components, discriminating between noise and actual signs of "materials illness", especially when coupled with materials and components' digital twins (Kreuzer et al., 2024).

For materials discovery or development AI-driven algorithms are used to identify new materials with desired properties, by analysing vast datasets of materials features (e.g. composition) and their corresponding properties, to significantly speed up the discovery or development process (Gupta et al., 2023; Yu et al., 2023).

For fabrication and manufacturing process optimisation, ML models are used to identify the best set of relevant production parameters to provide the desired properties and ensure reproducibility (Ciccone et al., 2023; Boobalan et al., 2023). This is especially important in the case of advanced manufacturing processes such as additive manufacturing (3D printing), but may also find application in the optimisation of traditional metallurgical processes (e.g. thermal treatments), by predicting the outcome of changing parameter sets and reducing experimental trials.

AI models can also be used to predict material properties and their evolution (generally degradation) during operation, based on examples of measurements and testing. Examples are thermal conductivity (Bhandari et al., 2023), radiation resistance and mechanical strength (Ferreño et al., 2021). This is important whenever the management of the lifetime of materials and components needs to be optimised. In these applications, one can distinguish, like in other applications, different underlying philosophies:

- "Brute force": a large number of data on a given property (e.g., embrittlement of reactor pressure vessel steels under irradiation, measured as increase of the ductile-brittle transition temperature) are used to train the system to predict it, given a set of predefined variables that are generally always known (e.g., in the same example, radiation fluence and flux, temperature, and material composition) (Jin et al., 2019; Ferreño et al., 2021; Bhandari et al., 2023).
- "Physics-informed": machine learning methods are trained by providing not only examples of correlations between the values of a given set of variables and the property of interest but also physical information in support of the correlation, often concerning microstructural material features, which, however, may not be easy to obtain for any material (so in some cases they may be provided by more or less reliable physical or semi-empirical models) (Bharadwaja et al, 2022; Zhu et al., 2022).
- "In support of physics": machine learning is used to "close the gap" between the underlying complexity of the structure of materials and the resulting properties and behaviour, for example by developing machine learning interatomic potentials based on the first principle calculation input, which are then used in a physical model (e.g. molecular dynamics) to calculate the properties of the material of relevance or to simulate their evolution in time (Anstin & Isayev, 2023); or else by providing physical quantities such as energy migration barriers as functions of the local atomic environment (Castin & Malerba, 2010).

The combination of ML-improved predictive capabilities with the ML-driven analysis of the input from sensors to test non-destructively materials and components in operation, to monitor the evolution in time of specific materials properties, can find its synthesis in the form of digital twins (Kreuzer et al., 2024). These enable the monitoring and prediction of the behaviour of materials and components in service, thereby optimising the lifetime management of the corresponding devices.

Electrical grids

Energy is a high-risk sector, and there it has been using, for many decades, expert systems (ES) as the core AI technology due to a) its structured and organised 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 energy storage used in the electricity power system were also reviewed (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 Centres 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 centre (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 optimisation, 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); the prediction of the distribution network faults that are likely to occur under specific circumstances related to past storms, including their respective repair duration based on historical data of past storms and actual fault occurrences during storms (Vähäkuopus et al., 2019); or, a data-driven system that provides personalised 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 (DL) 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 (Le réseau de transport d'électricité), 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 to aid human operators in operating electrical grids during normal operations and when the system is under stress due to overloads or disturbances. A similar industry-driven approach is being followed by the HORIZON European projects AI4REALNET (*"AI for REAL-world NETwork operation"*) and AI-BOOST (*"Artificial intelligence for better opportunities and scientific progress towards trustworthy and human centric digital environment"*), 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).

Energy system modelling

The field of energy system modelling is a well-established research area and has for decades utilised optimisation methodology to find both the optimum mix of capacities (capacity expansion modelling) and the optimum operation of a given capacity mix (operational modelling) [Chang 2021]. With the advent of AI methodology, the sector has gained another tool in its toolbox, and several review articles have been published on the application of these methods in the field [Ahmad 2021, Bordin 2020, Alabi 2022]. As the modelling field is large, and the potential applications of the models vary both in function, timeframe and geographical scope, so does the application of AI techniques. A general trend in the field is that the models are increasingly utilised for the study of systems with ever stronger cross-sectoral interaction (electricity, heat, gas), larger shares of non-regulated renewable power generation, stronger utilisation of storage technologies on both short and long term scale and a strong drive towards decarbonised energy systems. AI may aid in all of these aspects, but the field has yet to see the methodology penetrate the field, and more traditional optimisation and decomposition methodologies still dominate. There are, however, experiments with production estimation, storage utilisation optimisation, demand-response quantification, automated market participation, or dynamic infrastructure utilisation that show promising results.

The application of AI methods is hampered by data quality and abundance issues as well as large shares of proprietary or restricted data, high input dimensionality and complex system behaviour with large fluctuations, and the non-transparent black-box nature of the model. Although there is work being carried out on several of these fields such as explainable AI, the current status is still hampering the application of these technologies. The field is also challenged by a lack of competent and experienced experts in the field and a general lack of familiarity with the possibilities among decision-makers.

Even given these challenges the application of AI technology is expected to play an increasing role in the planning and operation of the energy system. EU has outlined their view on this in the study "The Role of Artificial Intelligence in the European Green Deal (europa.eu)", where specific regulatory actions are recommended to aid the utilisation of the technology toward the fulfilment of Europe's climate targets.

The electricity market

In electricity markets, AI has been increasingly applied across a range of functions, including forecasting electricity load, optimising electricity production, estimating prices in wholesale electricity markets, and enhancing grid management. First, AI is employed to forecast electricity demand (Raza and Khosravi, 2015; Nti et al, 2020). Accurate demand predictions are very crucial because they help balance market supply and demand, prevent shortages, and minimise costs. For forecasts, AI algorithms utilise historical data on energy demand, climate data, and customer behavioural patterns (Antonopoulos et al., 2020). Second, AI-based home and building systems improve energy use efficiency. By analysing real-time data, AI optimises energy consumption patterns (Shareef et al., 2018). This helps reduce peak load stress on the grid. Regarding the grid, AI is also used to manage decentralised grids with renewable energy sources (Zhou et al., 2019). Production from solar and wind is volatile in terms of the time of the day, the season, weather conditions, and grids fed by these sources, making the management of the grid challenging. AI can monitor and adjust in real-time, which maintains stability (Omitaomu and Niu, 2021). AI is also applied to predict electricity prices for electricity trading in wholesale markets (Ye et al., 2019). Dynamic pricing mechanism, supported by AI, leads to more effective bidding strategies. Moreover, AI is used to predict failures in equipment by following their patterns, by which maintenance becomes more effective in terms of cost and time (Cheng and Yu, 2019).

There are several laws, directives, and regulatory frameworks in the EU that directly or indirectly influence AI use and digitalisation in electricity markets. Among them are the Electricity Market Regulation, Renewable Energy Directive, Network Codes and Guidelines, Energy Efficiency Directive, and Energy Performance of Buildings Directive. For instance, the Electricity Market Regulation and Network Codes and Guidelines encourage the use of digital tools, including AI. While the former focuses on establishing an integrated, competitive, and consumer-centric electricity market across the EU, the latter sets the technical rules for managing electricity grids. The Renewable Energy Directive promotes smart grid technologies and energy storage systems that benefit from AI applications. The Energy Efficiency Directive and Energy Performance of Buildings Directive support the use of smart technologies to improve the energy performance of buildings.

The EU's approach to AI in the electricity market can be viewed from both positive and cautionary angles. On the one hand, aligned with the EU's climate goals, AI is expected to play a crucial role in reducing the carbon intensity of the electricity sector by optimising the integration of renewable energy and enhancing carbon capture technologies. The EU emphasises the importance of digitalisation, including AI, to create a more flexible and efficient energy system. For example, the Clean Energy for All Europeans Package supports the integration of AI to optimise energy use and improve market design, while the European Green Deal encourages AI applications to increase energy efficiency and reduce emissions.

On the other hand, the EU stresses the need for transparency, cybersecurity, and ethical AI usage. First, the Data Governance Act promotes secure data sharing in energy markets, which is crucial for AI applications that rely on large datasets to function optimally. The European Data Strategy further supports the development of energy data spaces, where AI tools can analyse and optimise energy systems more effectively. Second, the NIS2 Directive (Network and Information Security) highlights the protection of critical infrastructure, including electricity markets. AI systems in this sector must comply with cybersecurity standards to safeguard grid operations from cyber threats.

Further advancements in AI present many opportunities for electricity markets. For instance, to achieve more accurate predictions of weather, AI will enhance the integration of renewable energy into the grid, improve the effective management of energy demand in homes and buildings, and facilitate the management of storage systems. More advanced AI algorithms might also improve peer-to-peer energy trading and microgrid operations. By doing so, a decentralised energy system based on prosumers can be optimised (Hua et al, 2022). Furthermore, the usage of blockchain technologies to provide decentralised energy trading platforms can make transactions more secure.

Technology perspective

There is a plethora of use cases in which AI has been applied to the energy sector. The reader can consult (Hoffmann et al. 2022, Wang et al. 2024), for example. In this section, some fields will be analysed to illustrate the impact of AI on them and how it is pushing efficiency in the energy sector.

Nuclear materials

The use of artificial intelligence techniques, particularly machine learning, in energy materials science has many pitfalls, which are obviously common to other applications. The ways to avoid these pitfalls, or minimise their consequences, will likely determine future trends, after the initial exponential growth of ML applications.

ML models rely entirely on data quality and quantity. Both of these are not often guaranteed in materials science. Data quality can be an ill-defined parameter, given that the quality of a data point in a data set might be time-, technique- and purpose-dependent. High-quality data obtained twenty years ago might not be considered of high quality by current standards, while for example, the same micrograph might be very useful to deduce information on a given type of microstructural feature, but not on others. Or else, the same measurement or testing technique, applied in different laboratories, by different operators, according to different practices or standards, may not provide results that are consistent with those of other laboratories, operators and practices or standards, thereby preventing their safe inclusion in the same dataset. Alternatively, the same type of information or property may be biased by the technique used to obtain it, be it experimental or computational. On the other hand, depending on the measurement or testing technique, data production may be a very time-consuming process. The latter problem often leads to the need to include in the training dataset also old, inconsistent, or biased data, because of a lack of better sources, thereby increasing the probability of incorrect or imprecise predictions. Because of these difficulties, it will take time before ML techniques can be routinely used indiscriminately in all fields and instances of materials science. For this to happen, standards or at least best practices need to be defined for all techniques used to produce data. Alternatively, or in parallel, these techniques need to be replaced by other, faster ones, preferably non-destructive, that enable the production of large sets of consistent data (high throughput) that are predictors of the results of using the slower techniques. However, the representativeness of these measurements as predictors of other properties, or substitutes of other techniques, needs to be proven a priori. Yet another alternative is to use machine learning techniques that can provide reasonable predictions also starting from a limited set of data (few shot learning - Song et al., 2023). Thus the foreseeable trends of success will be constrained to machine learning applied to either newly produced data in a high throughput scheme, or any way consistent with each other because of the existence of standards (e.g. mechanical properties), or else to potentially limited data sets obtained in a fully consistent way, using few-shot learning. Thus, despite the vast potential of machine learning techniques in materials science, its applicability will end up limiting itself, because it will not always be possible to comply with these constraints. Reliable methodologies to recover and safely valorise old materials data will also need to be developed and applied.

The "black-box" nature of many AI models makes it challenging to interpret how they arrive at certain predictions. Another issue is the danger of poor generalisation of AI when applied to new and never seen data, as a consequence of overfitting to specific datasets. Both these issues can be a serious barrier in many critical fields where the safety or reliability of costly components is involved because they both prevent safe extrapolation. It seems therefore reasonable to think that the widespread "brute force" approach that is currently being applied almost by default in most cases will be progressively replaced by "physics-informed" approaches, as the only sensible way to partially remove the black-box nature of AI predictions, as well as to limit the possibility of overfitting to specific (and perhaps biased) datasets. Once again this will likely lead to a self-limitation or to a slowing down of the growth of applications of AI to materials science, due to the need to identify in each case the suitable physical inputs and to make sure they can be provided in a reasonable amount of time, so as to have sufficient data. This will be more or less feasible on a case-by-case basis.

Finally, another serious problem is the computational and energy cost of AI. Training sophisticated AI models requires significant computational resources, which may not always be available, and the energy cost that goes with it. Were AI approaches widely applied without control, a self-limitation to the actual use of these techniques would appear once again at some point.

Despite these limitations, but also based on the solutions they require, it can be expected that over the next decade and beyond there will be a race towards the as-wide-as-possible application, whenever feasible, of ML for the discovery and development of materials, as well as for the optimisation of fabrication techniques, by setting up so-called materials acceleration platforms, or adaptations of this approach to the specific cases of interest. In addition, ML will enter more and more forcefully the materials modelling world, initially mainly using brute force approaches, then more and more in combination with, or in support of, physics-based approaches. Finally, intelligent digital twins will become widespread tools for the lifetime management of materials and components in all energy devices that require optimisation, either for economic or safety reasons. The real, final and unambiguous, limiting factor to this foreseeably exponential growth will be the actual cost, in terms of resources and energy needed, of the widespread use of AI. Only in a world of almost inexhaustible, abundant, sustainable and cheap availability of energy can the use of AI proliferate freely. Interestingly, however, AI is expected to play a role in accelerating the path towards better energy materials, and thus to facilitate the development of a more efficient and sustainable energy landscape, thereby potentially self-supporting its own proliferation.

Electrical grids

Over the next decade, AI integration in power system control rooms will likely follow an AI-assistant interaction model, where AI-based systems provide ahead-of-time (e.g., day-ahead) or real-time recommendations of remedial actions to human operators who then take manual actions (Marot et al., 2022). This requires that AI models own meta-awareness, enabling them to recognise situations beyond their capabilities and seek human assistance (Endsley, 2023).

Unlike traditional model-based tools, which suffer from slow computation limiting near real-time application and difficulty handling uncertainties or missing inputs, AI-based solutions offer rapid real-time computation and can create proxy models for simulation functions that struggle with large scenario volumes (Duchesne et al., 2020). In this context, foundation models (FM), leveraging the growing availability of open data and advanced synthetic data generation techniques, can facilitate the real-time resolution of optimisation problems like optimal power flow (Piloto et al., 2024). Other applications for FM are energy time series forecasting and simulation (Gao et al., 2024), and various open libraries, such as TimesFM (Das et al., 2023), are emerging. However, access to computational resources is crucial for training extremely large transformer models, and the associated carbon footprint is significant. Another interesting advance in generative AI is diffusion-based models, typically used in image and video generation, which can also be applied to uncertainty modelling of complex systems (e.g., power systems). A notable example from other domains is the use of diffusion models to generate weather ensembles (uncertainty trajectories) in the ECMWF's data-driven forecasting system, achieving forecasting skills comparable to the ECMWF's physically-based model.

However, model-based approaches and domain knowledge will always be valuable assets and can be combined with data-driven methods. Neuro-symbolic learning (Bhuyan et al., 2024) is a promising approach to leverage heuristics, expert knowledge, and physical equations of the system as an initial coarse solution that improves as data-driven learning progresses. This knowledge can be used to guide the learning process, reducing the required data and training time, and during deployment as an initial solution that the learned model can further refine, thereby enhancing performance in low-data scenarios. An example is the data-driven augmented expert system proposed by Bessa et al. (2024), which encodes expert rules in a domain-specific language and uses evolutionary strategies to evolve the symbolic model through data-driven interactions between the control agent and the environment, optimising power distribution between high-energy and high-power energy storage devices.

AI and energy efficiency in industries

A close look at the development of energy solutions over the last two decades immediately reveals how energy efficiency strategies have changed dramatically. The advent of increasingly reliable and efficient cogeneration plants around the 1990s, the use of photovoltaic panels whose efficiency has allowed them to be used for industrial purposes, and the realisation of solar and thermodynamic solar systems combined with ORC plants without neglecting energy production from grids (gas and electricity) have led to today's energy systems defined as polygeneration.

As a result, we call today's energy systems 'complex energy systems', so the variables required for their energy optimisation increase, and the interconnections between them increase. The trade-off procedure also shows that their performance is often antagonistic to the proposed optimisation criterion. This implies that the variation of a variable does not always have the desired effect on the system.

In modern industrial contexts, therefore, the optimisation of the 'energies' required for the production process is linked to the multiple variables to be controlled. Moreover, the target (economic and/or environmental) to be achieved is itself antagonistic to some of these variables. The analysis of trade-off criteria is the basis of the study of expert and/or artificial intelligence systems (hereafter AI).

It follows from the above that a trade-off process, in a polygeneration system, could aim at maximising PES (Primary Energy Saving), reducing SPB (Simple Pay Back), the control of pollutant emissions, the reduction of CO2eqv emitted into the environment, maximisation of production, among others.

The question must be asked as to which methods are most appropriate for achieving what is now indicated. In view of the interconnectedness of the variables, it is not possible to choose a single method, but it is necessary to operate with an 'intelligent' approach to work on a multi-variable system.

AI may be an answer to what has been said so far. The genesis of an artificial intelligence system is, to a first approximation, an expert system, i.e. a knowledge-based system. This implies that each stage of an industrial process must be 'discriminated' to be able to artificially reproduce the performance relative to a given goal. The aim is to put in place an inductive or deductive process that enables the achievement of a trade-off, which, in our case, is relative to a complex energy system.

It should also be emphasised that AI requires a preliminary analysis phase, which is much more complex than the subsequent ones, through which the user can recognise the level of independence (presence or absence of interconnections) and sensitivity (overall energy weight to be optimised) among the variables to achieve the set objective.

AI is based on rules, methods, and sensitivities (rule activation parameters) that are the substrate on which to develop learning and arrive at an algorithm, e.g., by means of a neural network, that can have machine learning (hereafter ML) capabilities and deep learning.

The knowledge base is dictated by the sensor systems used to monitor the variables to be controlled. The data represent the discrete conclusions that the system reaches at the specific sampling time. The knowledge base is entrusted with the deductive rules that allow the system to follow logical reasoning on a particular operation: the base is updatable and allows the system to remain complete.

Rules can be addressed by using advanced genetic algorithms such as MOGA II (Gimelli et al. 2019), in which a selected set of decision variables, (knowledge base), is given as input variables. Once the objective functions to be optimised have been chosen, the genetic algorithm repeats four distinct steps for each generation: for a given set of variables, defined as individual, the value of the objective function (fitness) is calculated, which allows the population to be sorted according to the Pareto front dominance criterion. Thanks to the sorting obtained, the best individuals can be selected, and a new population generated by means of recombination: each of these steps modifies the initial population and can be considered as an independent process. Typically, there is no single global solution, but rather a set of optimal solutions that are introduced into the knowledge base from time to time to assess their actual validity.

(Maulin 2021) use a different genetic algorithm to optimise parameters for multi-agent systems, eventually simulating the results in computer development environments such as Matlab Simulink to test their operation.

Objective functions, in cases where they are not directly determined by the minimisation and/or maximisation of simple control parameters, can also be obtained through the discrimination of multi-objective functions obtained with statistical regression models such as, for example, the stepwise method used for the characterisation of a production process. In this case, the authors' proposed idea is to discriminate the process to be able to apply optimisation algorithms.

Traditional approaches are based on multi-predictors of regression (Furno & Biswas 2015): statistical approaches are a good option to avoid the burden associated with engineering approaches when observed/measured data are available and linear regression analysis has shown promising results due to reasonable accuracy and relatively simple implementation compared to other methods (ARIMA) (Amber et al. 2015, Oliveira & Oliveira 2018).

In this context, the research work carried out by (Amoresano et al. 2023) proposes to increase the efficiency of two-phase heat exchange in vertical and horizontal pipes by adopting an accelerometer sensor to collect vibrational data within the hardware element. Statistical analysis made it possible to discriminate the vibrational pattern of the two-phase flow, which became the knowledge base of an expert system, the genesis of a non-invasive Internet of Things (hereafter IoT), for the remote control of abnormal operating conditions that could lead to thermal stress in the pipes affected by the fluid flow and thus intervene on the efficiency of heat exchange.

Turning to ML-based methods, the first approaches (Liu et al. 2020) which showed good results were based on Support Vector Regressors. (Giglio et al. 2023) propose an optimisation between photovoltaic modules and storage systems: dimensional variables are optimised so that through a study of real-time energy consumption, an ML module generates forecasts of demand in the near future. This led to a reduction in consumption without additional costs by implementing a control such that the strategy would exploit both photovoltaic production and the price of energy at the time of use.

(Agostinelli et al. 2021) promote the importance of digital twin approaches aimed at the realisation of an intelligent optimisation and automation system for energy management using a three-dimensional data model integrated with ML and AI. This approach is also followed by several other authors (Tao et al. 2019, Machorro-Cano et al. 2020, Liu et al. 2012).

(Ahmad et al. 2021) emphasise how the importance of intelligent development can be identified in four macro fields of industrial development: simulation and improvement (the simulation of the energy system where ML and AI are well suited to optimisation through the use of artificial neural networks); investment and markets; sustainability and security to optimise energy infrastructure maintenance programmes and activities. Finally, Customer Oriented Services offer services to consumers to participate in the energy system more easily.

According to (Shrouf et al. 2015), adopting smart systems achieved energy efficiency benefits by reducing machine downtime, and recording and reporting processes that do not add value to the finished product. This was done by using the load balancing method and considering variable energy prices as one of the main factors in defining machine scheduling.

In addition, the authors, convinced of the possibility of making a production system efficient by means of AI systems, are currently studying an expert system that can keep the efficiency of individual energy machines in the industrial field high, e.g., by reducing on/off cycles and consequent tension overloads, evaluating the predictive energy demand on a statistical basis and/or modifying the production mix, with the possibility of storing any excess energy and making it available at a later date.

Potential pitfalls and limitations when using AI

There are many challenges to the application of machine learning and data-driven modelling in the energy sector including a lack of data and operability, skills and knowledge, and trustworthiness.

The concept of trustworthiness of AI-enabled control of physical systems can be split into overall components (DNV-RP-0671 2023):

- Technical and performance-related aspects such as accuracy, correctness, robustness to changing conditions or noise, bias and uncertainty awareness.
- Explainability and interpretability cover the user's ability to understand the model prediction.
- Human oversight and interactions such as the possibility for humans to control and intervene in the system's operation.
- Safe and secure implementation ensuring that the system cannot lead to harmful situations and that outsiders cannot tamper with the model or the data.
- Transparency and privacy ensuring accessibility of relevant information about the system to authorised, including clear labelling of the system being considered an AI.

To address the first two components, it is crucial that machine learning is applied in connection with domain knowledge about the actual system. On the simplest level, this is a requirement to identify relevant relationships where a data-driven model will be beneficial, and which data can be used for training the model (Karpatne et al. 2017). On more sophisticated levels, one can for example combine deep neural networks with partly known physical models in the form of differential equations within the framework of Physics Informed Neural Networks (PINNs, Raissi et al. 2019). These are, however, only soft-constrained models which are not guaranteed to adhere to the laws of physics. Such guarantees can in some cases be implemented through Hamiltonian formulations (Greydanus et al. 2019), where basic physical properties such as energy are guaranteed to be conserved (or exchanged, Desai et al. 2021, Eidnes et al. 2023). An alternative for conserving relations between various properties in the system, e.g. an electric grid, is the application of graph neural networks (Battaglia et al. 2018, e.g. used in Sheikh-Mohamed 2023 for probabilistic power system operation). Also, temporal and spatial development can be coupled by choosing smart neural network structures (Williams et al. 2024).

Combining or constraining the data-driven model with domain knowledge will, in many cases, lead to a more robust model with explainable behaviour and following the domain knowledge outside of the provided data range while exploiting the flexibility of the data-driven framework to account for factors that are often simplified in the existing models. Hence, it contributes to trustworthiness, but it is not a sufficient condition.

Another important aspect is the transfer of knowledge. As the IEA states (Bennett & Spencer, 2024), identifying a new material for an energy application via a computer-based method is less than half of the innovation task. Prototyping, followed by commercialisation, mass manufacturing and widespread market uptake, can take years or even decades.

Yet other AI-related tools in development could compress these timetables, too. Thus, digital twins can play a role. They have been used to optimise manufacturing for over a decade but are now being powered by AI and applied to innovation. However, difficulties also persist in applying AI to this phase of the innovation process. Currently, these tools are not all widely accessible to innovators in the scale-up stage and some digital gaps remain.

Trustworthiness

Trust among humans is based on mutual understanding and common values such that the behaviour of another person is within one's expectations. It is only human that we consider an AI to be "trustworthy" if it yields intelligible results. Since putting (parts of) our energy systems, which are critical infrastructure, into the hands of AI clearly poses a "high risk", AI in energy research may be classified accordingly by the EU AI Act. Hence, regulatory requirements for AI focus on transparency and accountability. This starts with FAIR and robust data (Wilkinson et al. 2016) and continues with the deployment and life cycle of explainable AI (Saranya et al. 2023).

The requirements set by the AI Act on explainability are binding but remain abstract, which is why detailed, harmonised standards are the subject of current work (Walke et al. 2023). For example, the international standardisation committee ISO/IEC JTC1/SC 42 "Artificial Intelligence" aims to define objectives and approaches for explainability and interpretability of ML models and AI systems (ISO). However, there is currently no metric that takes all regulatory requirements into account (Sovrano et al. 2022), especially those of the energy sector.

In any case, AI-based applications could make errors in judgment, act unpredictably, and be tricked by adversarial attacks. Thus, making AI trustworthy in a systematic way is highly important in critical infrastructure workflows like the power grid. On top of satisfying basic performance metrics, AI needs to satisfy requirements related to reliability and transparency and have ethical adherence and robustness from a social-technical perspective. For instance, the Horizon Europe AI4REALNET project follows a socio-technical system design about the joint optimisation of humans, technology, and organisation to optimise the overall system's performance. It defined a set of *desiderata* to build human trust in AI-based decision systems (Mussi et al., 2024), such as:

- a careful allocation of functions between humans and AI is required to avoid negative impacts on human performance and to enable synergies between humans and AI that go beyond the capabilities of humans and AI alone;
- while explainability is essential, it is only one form of providing automation transparency. Others are exploration, animation, mirroring, or intuitive interface design;
- the analysis and design of AI, human-AI interaction, and human-AI collaboration require cognitive engineering methods that can model the decision-making process and requirements for function allocation resulting from human cognitive processes related to decision-making, learning, trust, and motivation.

Furthermore, the Assessment List for Trustworthy AI (ALTAI) framework[1] created by the High-Level Expert Group on Artificial Intelligence (AI HLEG) appointed by the European Commission was used to identify the relevant risks and ethical concerns. Noteworthily, the ALTAI has been conceived as an assessment instrument for ex-post self-assessment of AI systems. AI4REALNET proactively uses its structure to perform an ex-ante assessment of the use case definition. This allowed to:

- identify risks and ethical issues particularly relevant to the considered AI use cases,
- define use case requirements to be fulfilled by the AI solutions developed,
- and to develop suitable metrics to validate that these requirements are appropriate and sufficient to mitigate the identified risks and ethical concerns.

For further reading, the reader is referred to the DNV recommended practice (DNV-RP-0671 2023) as well as intermediate results from the THEMIS 5.0[2] and TEA-DT[3] projects.

The human-centric approach: Harnessing AI in social research and the benefits for the energy sector

The energy sector is undergoing a significant transformation, with Artificial Intelligence playing an increasingly crucial role in areas like grid management, energy forecasting, and optimising energy consumption (Ahmad et al. 2021). The growing decentralisation of the energy system—through the introduction of collective models, energy sharing, and localised production—makes human-centric participation more and more important (Pogmore & Wheeler 2023). Different households exhibit unique dynamics and behaviours that require careful coordination to maximise utility and optimise energy consumption. The integration of AI into social science offers a powerful solution to address these challenges. By enabling advanced data analysis capabilities, AI can create personalised

[1] https://futurium.ec.europa.eu/en/european-ai-alliance/pages/welcome-altai-portal
[2] https://www.themis-trust.eu/results
[3] https://www.turing.ac.uk/research/research-projects/trustworthy-and-ethical-assurance-digital-twins-tea-dt

tools and simulations of system interactions. The latest is particularly true due to the constant increase in computational power that facilitates complex system modelling (Hwang 2018). This allows for predicting energy consumption patterns and optimising energy use across the entire system. Moreover, AI's proficiency in natural language processing facilitates smoother interactions with humans, making it easier to incorporate human input into energy management systems. AI also serves as a catalyst for centralising human involvement in production systems, paving the way for Industry 5.0 (Alves et al. 2023), where human expertise and advanced technologies work hand in hand to create more efficient and sustainable energy solutions.

In this rapidly evolving context, adopting a human-centric approach supported by AI is crucial for effectively managing and optimising modern energy systems. This approach ensures that these systems are not only technologically advanced but also closely aligned with the needs and behaviours of the people they serve.

As part of this communication, we highlight up to four AI-enhanced capabilities for social science research that make user-centric approaches in the energy system more actionable.

- Tailoring: Data processing capabilities enabled by AI and machine learning modelling enhance the generation of user profiles, essential for creating archetypical categories for personalised intervention programmes and energy-saving strategies, as well as maximising grid flexibility based on energy consumption patterns (Gržanić et al. 2022). AI and machine learning techniques streamline analysis, allowing faster and more efficient profile creation and updates with new data. This is crucial for developing dynamic interventions and strategies that evolve with user needs, tailored to the specific characteristics of different user groups (Méndez et al. 2023), including those facing energy poverty (Primc et al. 2019). Furthermore, AI and machine learning facilitate the analysis of adoption capabilities for new distributed energy resources (DER) such as photovoltaic systems (PV) (Alipour et al. 2021), electric vehicles (EV) (Lagomarsino et al. 2022), and heat pumps (HP) (Oikonomou et al. 2022). They can also aid in understanding market dynamics, including dynamic pricing based on consumption patterns (Gržanić et al. 2022).
- Generation of expert models: Traditional AI systems, while powerful, can sometimes lack the human context and understanding crucial for complex domains like the energy sector. This is where AI excels at generating "expert models", bridging the gap by integrating valuable human knowledge with AI's processing capabilities (e.g., Human-in-the-loop machine learning). Expert models leverage human expertise to capture the intricate dynamics of energy systems, including identifying barriers and developing strategies to promote proper energy use and local generation. These models simulate various scenarios to assess the potential impact of different policies on user behaviour and system performance, employing a "what-if" approach to test solutions for problems with uncertainty or vagueness (Suganthi et al. 2015). The choice of the expert model tool depends on the specific problem being addressed (Frangopoulos 2009). For instance, rule-based systems are ideal for well-defined problems with clear rules or conditions, often used for diagnostics and basic decision-making tasks; fuzzy logic systems are suited for situations involving uncertainty or vagueness, mimicking human reasoning for flexible decision-making; knowledge-based systems tackle problems requiring complex reasoning and extensive codified knowledge; and neural network systems are powerful for handling large datasets with intricate patterns, useful when problems involve noisy, unstructured data or lack explicit rules.

- System modelling: AI is fundamentally reshaping how we model energy systems. By crafting virtual replicas in controlled environments, AI tools unlock the power of agent-based modelling. This approach goes beyond traditional methods by simulating nuanced, intricate interactions between social and environmental components. These interactions can be complex, non-linear, and dynamic, mirroring the real world (Polhill et al. 2016). Furthermore, AI allows us to integrate existing knowledge about the system into the model (Davis et al. 2019). This is achieved through simulations that factor in the behaviour of individual actors within the system, leading to more accurate and realistic outcomes. The model's ability to represent diverse actors (households, businesses, policymakers) and their interactions becomes crucial for understanding how the entire system might change (Polhill et al. 2016). Policymakers, among other actors, can leverage these AI-powered virtual testing grounds to validate new strategies, optimise them for public acceptance before real-world implementation, and pinpoint key leverage points for interventions that can promote positive systemic change within the energy sector.
- Diffusion maps: Machine learning techniques excel at using AI to generalise the characteristics of diverse entities, such as households, enterprises, or industries, based on limited real-world datasets. This capability enables the extrapolation of existing user profiles that are statistically representative of a broader geographical area, allowing for the scaling up of insights without requiring extensive new data collection (Polhill et al. 2012). By leveraging existing model outputs, this approach offers several advantages, including privacy protection through the use of synthetic data, scalability, speed in generating profiles, and actionable insights for energy stakeholders. These insights can identify areas with high potential for distributed energy resources, facilitate collaborative programmes between providers and consumers, and develop strategies to encourage more efficient energy use (Alipour et al. 2018). This method can also be used to identify regions most affected by energy poverty, enabling targeted interventions to assist vulnerable populations (Mashhoodi 2019).

Several benefits can be derived from the use of these AI-boosted techniques in energy systems:

- Empowering consumers: Empowered consumers benefit from personalised energy-saving strategies that align with their lifestyles and preferences. This approach helps them reduce energy costs, enhance comfort, and actively participate in managing their energy usage, leading to greater overall satisfaction and agency.
- Ensuring transparency and trust: Energy systems that are transparent and trustworthy infuse confidence among consumers and businesses. Through clear communication and reliable practices, such as explanatory interactive learning (Teso & Kersting 2019), users and stakeholders can make informed decisions, provide feedback, and feel secure in managing their energy resources, thereby nurturing long-term trust.
- Enabling collaborative models: This requires fostering partnerships and cooperation among stakeholders to optimise energy management, reduce costs, enhance innovation, and optimise resource use through collective efforts and shared resources.
- Generating grid resilience: Resilient energy grids provide reliable and uninterrupted energy supply, even during disruptions. This resilience reduces downtime, supports economic stability, and ensures continuous service for consumers and businesses, enhancing overall reliability and energy security.

- Facilitating equitable energy access: Equitable access to energy resources ensures that all communities have reliable and affordable energy options. Addressing disparities and promoting inclusive energy policies are essential steps toward achieving this goal.
- Promoting energy system efficiency: Efficient energy systems optimise resource usage by analysing consumption patterns and encouraging responsible practices to lower costs, minimise environmental impact, and improve production and distribution efficiency.
- Improved decision making for policy optimisation: Data-driven decision-making improves policy outcomes and resource allocation, enabling policymakers to develop effective strategies that meet targeted goals, such as sustainability and economic benefits, more efficiently.

Table 1: Table summarising the benefits enabled by different AI capabilities in the research domain for energy systems from social sciences. The plus (+) symbols are arbitrarily used by the author to indicate the varying levels of impact of each AI capability in generating benefits.

AI capabilities for User-centricity	Tailoring	Expert models	System modelling	Diffusion maps
Empowering end-consumers	+++	+	++	++
Ensuring transparency and trust	+	++	+	++
Enabling collaborative models	+++	++	+++	++
Generating grid resilience	+	++	+++	++
Facilitating equitable energy access	+++	++	+++	++
Energy system efficiency	++	++	++	+++
Improved decision making	++	+++	+++	+++

Additionally to all of the previous, the use of generative AI tools emerges as a new option that society is quickly adopting and profiting from. Proven a wide set of new capabilities already described, they also present new challenges that must be properly approached, in particular, the provision of training capacities for reducing the learning process for their correct exploitation and the social awareness of the likelihood that the results of the generative AI present does not necessarily mean demonstrated truth and trustworthiness. In this context, initiatives such as the EC's Pact for skills can be cornerstone.

In conclusion, the integration of AI into the energy sector, particularly through the lens of social science, offers transformative capabilities that are essential for managing and optimising modern energy systems. AI enhances user-centric approaches by tailoring personalised energy strategies, generating expert models that combine human knowledge with data analysis, creating sophisticated system models, and developing diffusion maps that generalise insights across diverse populations. There will be difficulties to overcome, but this human-centric approach is pivotal in navigating the complexities of the evolving energy landscape, paving the way for a future where advanced technologies and human expertise work hand in hand to achieve greater social and environmental benefits.

For further insights on this topic, a McKinsey expert discussion can be consulted in the references section.

AI in the scope of EERA: some success stories

Renewable energy forecasting

The model chain for renewable energy sources (RES) forecasting is well-established in industrial applications and is currently available as a commercial product. This product typically integrates a numerical weather prediction (NWP) model, which forms the physical layer of the forecasting model chain, with post-processing and a machine learning model (AI layer) to convert weather variables into power predictions. According to a recent survey conducted by CIGRE Working Group C2.42 involving approximately 50 system operators, AI is already used in operational RES forecasting systems (Cremer et al., 2024). This demonstrates the successful application of AI in system operations, and it is being integrated into various power system operation functions and RES market bidding activities. These include procuring balancing services, week-ahead operational planning, and defining remedial actions for extreme weather events (Fox et al., 2021).

In the physical layer, AI has been exploited for data assimilation between the physical model of the atmosphere and data collected from assets like wind turbines, with some improvements in predictability in the first 3-4 hours (Shaw et al., 2019). An alternative is purely data-driven weather models, where two notable examples built using graph neural networks are GraphCast (from Google DeepMind) and AIFS (from ECWMF). In the AI layer, tree-based methods like gradient-boosting trees and random forests have outperformed competitive approaches based on deep neural networks and variants. This has been shown in benchmark competitions, such as the Global Energy Forecasting Competition 2014, and it was recently shown again in an operational competition promoted by the IEEE Working Group on Energy Forecasting and Analytics that benchmarked in a real-environment forecasting system developed by industry and academia (Browell et al., 2023).

Bioenergy

Most of today's biogas power plants, which are commonly part of an agricultural business or consortium of some kind, produce energy and heat in a continuous mode of operation. At the same time, differential and algebraic equation-based models for anaerobic digestion processes inside a plant's reactor have been found unsuitable for industrial applications due to their idealisation. However, AI techniques can model anaerobic digestion in full-scale and yield accurate estimates on the biomethane potentials even for industrial applications (Meola et al. 2023a). This opens up the possibility for both compensating more irregular renewable energy sources and optimising energy and heat production with respect to demand and/or market prices (Mauky 2018). A key challenge is the availability and interoperability of data, which is expansive to generate in experiments and with high variance due to the impurity of the used biomass substrates; e.g., straw and liquid manure.

Materials

It is well known that materials are an essential element of any innovation in the energy sector. However, discovering a new material that is both suitable for final applications and sustainable typically takes over ten years of experimentation and significant investment.

Enormous quantities of experimental data are being generated on the properties of these materials, stored in large thematic databases and scientific papers. Relating a material's structure to its function needs to be accelerated, as the search space is vast. Many materials are still found empirically, with candidates making and testing a few samples at a time. This process is subject to human bias, as researchers often focus on a few combinations of elements they find interesting.

To address this, computational methods are being developed to automatically generate structures and assess their electronic features and other properties. Supercomputers can predict the properties of all known materials and solve very complex material models. However, translating this data into industrial and commercial applications is still a challenge.

Artificial intelligence (AI) and machine learning (ML) techniques can significantly speed up the discovery of energy materials by finding patterns in data sets. AI has already been used to predict the results of quantum simulations, identifying potential molecules and materials for flow batteries, organic light-emitting diodes, organic photovoltaic cells, and carbon dioxide conversion catalysts. These algorithms can predict results in minutes, compared to the hundreds of hours needed for traditional simulations.

Despite this progress, challenges remain. There is no universal representation for encoding materials, and different applications require different properties, such as elemental composition, crystal structure, and conductivity. Well-curated experimental data on materials are rare, and computational tests often rely on assumptions and models that may not accurately reflect experimental conditions.

To overcome these challenges, the machine-learning and energy-sciences communities should collaborate more closely to exploit AI and ML techniques. AI can analyse large amounts of data and predict the properties of new materials, reducing the time and costs associated with traditional experimental methods. By harnessing AI-driven simulations and data analysis, researchers can identify promising materials more efficiently, cover the multiscale design from atoms to real materials, and optimise their properties for specific energy applications while ensuring sustainability. This paradigm shift not only increases the pace of materials discovery but also opens up new possibilities for creating advanced materials that meet the evolving needs of the energy sector (Aspuru-Guzik & Persson 2018).

To progress in the field of accelerated materials discovery, materials scientists should organise their data into curated, standardised, and machine-readable forms. Moreover, scientists should collaborate to develop materials acceleration platforms (MAPs). MAPs are platforms where experimental and computational laboratories work together in an automated manner (the reader can consult the current developments made by the COST Action EU-MACE).

The energy consumption that AI produces

Which problem are we talking about

The energy cost of AI is significant, with data centres becoming increasingly energy-intensive. According to the International Energy Agency (IEA), data centres worldwide currently account for between 1% and 1.5% of global electricity consumption. The scientific community agrees that the rapid adoption of new technologies will substantially increase energy use in this sector.

Recent studies (Luccioni et al. 2024) indicate that handling hundreds of millions of ChatGPT queries can consume around 1 gigawatt-hour per day, equating to the energy usage of approximately 33,000 households. Training a single chatbot can use as much electricity as an entire neighbourhood consumes in a year. By comparison, traditional cloud computing workloads, such as online services, databases, and video streaming, are far less computationally demanding and require significantly less memory.

Among generative AI tasks, image generation is the most energy-intensive. Creating a single image using an AI model consumes the same amount of energy as fully charging a smartphone. Generating 1,000 images with a powerful AI model like Stable Diffusion XL produces as much carbon dioxide as driving a petrol-powered car for 6.6 km. In contrast, text generation is less energy-intensive; generating text 1,000 times uses only 16% of a smartphone's full charge. Each AI-generated prompt, multiplied by 1,000, results in CO2 emissions equivalent to driving 1 meter.

Studies have shown that large generative models, used for tasks such as question answering, text generation, image classification, subtitling, and image generation, require significantly more energy than smaller, task-specific AI models. For instance, using a generative model to rank film reviews by positivity consumes about 30 times more energy than an optimised model designed for that specific task. The higher energy consumption of generative AI models is due to their multifunctional nature, handling multiple tasks like generating, classifying, and summarising text simultaneously, rather than focusing on a single task.

The rise of generative AI has led major technology companies to integrate powerful AI models into a wide range of products, from email to word processing, as seen with Microsoft's Copilot in Bing and the Office suite. These generative AI models are now used millions, if not billions, of times daily. Moving forward, a more sustainable approach involves integrating specialised, less energy-intensive models into IT services, which can often perform better for specific applications. A step forward in this context might be DeepSeek, which claims to have reduced the energy consumption ten time providing similar results. Independently of the correctness of their solution in comparison to other generative AI models, DeepSeek has demonstrated that working on improving the algorithm part of the LLMs can reduce the energy consumption that AI produces.

Data science and AI for energy consumption in HPC infrastructure

Data centres (DCs) are the backbone of the ever-increasing need for reliable and scalable data processing, storage, and networking capabilities to support businesses and individual users. This is a direct dependence on computing power and chips performance that cannot be avoided. With the rapid growth in demand for digital services and associated applications, data centres have become ubiquitous, which underpins the ever-growing digitisation. In the meantime, they pose significant threats in terms of both energy costs and the associated carbon emissions (Vafamehr & Khodayar 2018). A new era has come with the energy consumption reduction of AI solutions like DeepSeek, but additional actions can be performed from the hardware side. Hence, the new developments that USA and China may approach to create new more efficient chips and processors from the energy side can result in a reduction in the emission of CO2.

The current global energy consumption of data centres is estimated to be approximately 3%. According to (Andrae 2015) and the late update in 2019 (Andrae 2019), given the rapid pace of digitisation, if necessary actions are not taken, data centres are expected to consume 21% of the global demand by 2030. However, if the necessary actions are taken, this figure can be reduced to 8%. Regarding environmental issues, DCs are estimated to contribute 0.3% of global carbon emissions annually (Jones et al. 2018) and are expected to increase to 8% by 2030 (Cao et al. 2022).

Optimising the energy efficiency of DC and in particular the class of High-Performance Computing (HPC) cluster is therefore a major concern. Demand for computing resources and thus energy demand for HPC is steadily increasing while the energy market transforms to renewable energy and is facing significant price increases. This could lead to significant operational costs, power security impacts in the energy ecosystem, and environmental threats. Integrating the IoT, sensors, and intelligent devices has significantly contributed to generating vast operational management data from various aspects of the data centre industry. Effectively modelling and processing this data could improve energy efficiency, ensure reliability, reduce operating costs, and sustainably manage data centres (Grishina et al. 2020).

However, prior heuristics, statistical, and engineering methods could not be effective for modelling and simulating this data. Meanwhile, a Data Science approach (Grishina et al. 2020. Grishina et al. 2022) ensures a better interpretation of energy consumption data (energy-thermal-computational data) to modelling Data Centre Energy Efficiency. Indeed, the data science approach (from raw data to decision making) uses several different techniques - such as machine learning, data assimilation, AI, etc.- to obtain value from the stored and collected data in order to provide an accurate picture of the DC consumption. Moreover, data science techniques (e.g. machine learning algorithms, data assimilation) can be used to understand the DC' users working style and predict the DC' thermal and energy weight.

Consequently, a complex analysis to optimise energy consumption (e.g., air cooling and computer systems) could be done. Useful analysis and utilisation of energy monitoring data are a key factor in the success of many business and service domains, including DC. The application of advanced data science techniques for energy data in DC has many benefits and challenges, including the step forward in terms of energy efficiency in DC framework and metrics as well as infrastructure management, which includes the reliance on cloud computing services, networks, and IoT technologies.

A structured framework of DC' energy consumption, based on energy data analytics could be used to quantify energy efficiency; it is necessary to understand the opportunities for improving energy efficiency in DCs. Furthermore, taking into account the introduction of HPC of the Graphics Processing Units (GPUs), the aim is also to investigate the energy efficiency issue of GPUs. GPUs are now considered serious contenders for high-performance computing solutions and an excellent tool for massively parallel computing. The use of GPUs in DC environments brought about a transformation in data processing and analysis for many enterprises. GPUs have also proven their worth as job accelerators and Virtual Desktop Infrastructure (VDI) is a noteworthy example. This may lead to power supply and thermal dissipation problems in computing centres.

Within the Open Lab (virtual and/or physic environment within research and industrial partners cooperate) namely "Towards sustainable and energy efficient using Data Science implementations in HPC Data Centre " of PNRR-Rome Technopole, a collection of data science (e.g., data mining, machine learning, data assimilation, AI, ...) has been employed for the prediction analysis of energy consumption, thermal characteristics based on actual temperatures in a real ENEA-DC with CPUs and GPUs cluster rather than considering device setpoints or guidelines. In addition to that, it aims to understand and model user resource consumption behavior based on historical data to predict future consumption of resources: CPU, memory, and network.

This research within Open Lab aims to bring about improvement of DC energy efficiency for sustainable operations. Moreover, it will probe how and where modern GPUs are using energy during various computations, schematically manage the thermal difference between regular CPUs and GPUs, and then discuss different strategies and proposals to increase energy efficiency in the GPU context. So, a complex analysis to optimise energy consumption (e.g., air cooling and computer systems) could also be done with the help of a valuable thermal imaging camera for detecting critical points at a thermal level. Proper analysis and utilisation of energy monitoring data are essential to success in many business and service domains, including DC.

The application of advanced data analysis for energy data in DC presents many advantages and challenges, including the step forward in terms of energy efficiency in the framework and the management of thermal parameters that, managed optimally, can optimise energy consumption allowing a longer life cycle of the hardware. A structured framework of DC energy consumption based on energy data science could be used to quantify energy and thermal efficiency; it is necessary to understand the opportunities for improving efficiency in DCs with a mix of CPUs and GPUs. Using GPUs in DC environments brought about a revolution in data processing and analysis for many enterprises.

A significant challenge in the topic of energy efficiency data centre is provided by the digital twin approach (Chinnici et al. 2023). Indeed, a digital twin design for analysing and reducing energy consumption and also computing resources optimisation of a real-world HPC system is mandatory. Within the Open Lab namely "Digital Twin data centre" of PNRR-Rome Technopole, a digital twin is based on the HPC cluster at the ENEA HPC cluster namely CRESCO cluster in R.C Portici, Italy. The digital twin receives information from multiple internal and external data sources to cover the different optimisation opportunities. The digital twin also consists of a scheduling simulation framework that uses the data from the digital twin and real-world job traces to test the influence of the different parameters on the HPC cluster.

An analytical reporting system has been developed, "Analytical Dashboard", for the operation and energy management based on a data-driven AI-based framework for modelling data centre efficiency that learns from actual operational data. A dashboard will allow the management, monitoring, and (near) real-time visualisation of data related to real data centre using blockchain technology. Technology solution to implement the analytical dashboard: the hardware and software resources will be modelled as a digital twin. Blockchain and tokenisation technologies will be used to allocate computing resources (HPC loads) to optimise or efficiently distribute infrastructure energy consumption across various activities. This approach is exhaustively trained and tested using real operational data obtained from the ENEA-CRESCO6 cluster high-performance computing (HPC) data centre.

The digital twin approach is a promising method to provide extra data sets for training. Specifically, digital twins can not only provide physical characteristics of the DC system but also dynamically adjust scene parameters through programming (Kostenko et al. 2020). In this way, many samples are obtained to assist model training and improve fault tolerance. In Gartner's opinion, digital twins will proliferate industries, and when combined with AI technology, digital twins will enable open, connected, and coordinated intelligent spaces (Gartner 2015).

The seamless connection and real-time data exchange between the physical and digital twin allow for conducting real-time energy consumption simulation and energy-saving control. Therefore, the combination of AI technology and blockchain technology to build the digital twin is conducive to researching adaptive, intelligent, and fault-tolerant DCs energy saving schemes in a more flexible and dynamic way.

A future strategy

The ownership and control of high-performance computing (HPC) infrastructure are indeed critical factors in the development and advancement of AI models. Indeed, training advanced AI models, particularly large language models and generative models, requires substantial computational power. HPC infrastructure provides the necessary resources for parallel processing, high-speed data handling, and efficient memory usage, which are crucial for training these models effectively.

Thus, organisations with access to advanced HPC infrastructure are the only ones that can push the boundaries of AI research and development. Indeed, they can experiment with more complex models, larger datasets, and innovative algorithms, giving them a competitive edge in the AI sector.

The technological and economic competition has reached a high level of speed, and HPC infrastructure can significantly reduce the time required to train AI models. Faster training times mean quicker iterations, allowing for rapid development and deployment of AI solutions. In the past HPC infrastructures were considered very expensive to build and maintain, now their use can be more cost-effective for large-scale AI operations in the long run. Companies that own and operate their HPC infrastructure can avoid the high costs associated with cloud-based computing services for intensive AI workloads. Control over HPC infrastructure provides a strategic advantage. Companies can prioritise their resources for their projects, ensure data security, and maintain proprietary technologies without relying on third-party providers.

This technological race to possess the fastest and most powerful HPC infrastructure has overshadowed research activities in the field of Big Data and HPC and such a race can even speed up with the launching of new generative AI solutions that could reduce the dominance of companies such as NVIDIA. In fact, we are witnessing a race to build huge supercomputing infrastructures using microprocessors and technological solutions already available on the market. The consequence of this is that almost all HPC infrastructures are equipped with a huge number of graphics processors from the same company. This industry has effectively monopolised the microprocessor market and we depend on it to use AI models. Research in the HPC and Big Data sector, and in particular the development of more specialised and efficient AI models, needs to be given a new lease of life, as recently demonstrated. The energy sector is therefore called upon to think carefully about future developments in order to plan for the development of infrastructures and models that are of most interest to it and on which to focus in the coming years.

Last but not least, data centres (as many other critical facilities) consume energy under a 24x7 scenario, so the clean energy transition must also provide a new energy generation in which a continuous and reliable provision of power is ensured.

For a systematic comparison of the ongoing inference cost of various categories of ML systems, covering both task-specific (i.e. fine-tuned models that carry out a single task) and 'general-purpose' models, (i.e. those trained for multiple tasks), the reader can consult (Luccioni et al., 2024).

Conclusions

Not only the energy sector, but the whole society is moving to a digital scenario in which ICT technologies are the cornerstone. In particular, the impact of AI applications in the energy sector more broadly needs to be fully assessed. Promising examples are of utmost importance as they are accelerating breakthroughs in clean energy innovation, managing the electricity system to facilitate more renewables and easier decision-making processes, and deploying AI to enhance the profitability and speed of electrification programmes in developing economies. These applications could potentially transform energy systems, but today, their impacts, enabling conditions and scalability are not well known.

Concerning the electricity market, the European Network of Electricity Transmission System Operators (ENTSO-E) states that an AI approach can be implemented in "vast swathes of TSOs' core business to adapt a large amount of data, providing support for decision-making either from a system operation perspective or within corporate development and business administration".

In ENTSO-E's view, the main advantages and useful applications of AI for a TSO's core business might be established in one of the following: using deep learning (DL) in drones for maintaining overhead lines; applying digital twins (virtual representations) of high-voltage equipment of high importance; introducing software in controlling and accounting to improve administration performance within an organisation; and using optimisation code for automated energy trading (here, blockchain capabilities could play an important role, too). For the sake of completion, ENTSO-E categorises AI as having a Technology Readiness Level of 6 (i.e. demonstration stage).

On the other hand, both transmission and distribution system operators (TSOs and DSOs) must also consider the risks they may be taking in using AI from external suppliers, which needs to be addressed in terms of cybersecurity.

With respect to the digital gap, it is facing a two-fold challenge. On the one hand, there is a disconnect between the rapid pace at which AI is advancing and the understandably conservative pace at which new technologies are adopted by key energy industry actors; on the other, all the possibilities that AI is providing should be properly adopted and exploited by the final users.

Thus, the design and implementation of AI need to be conducted by multidisciplinary teams of professionals who combine a deep understanding of the AI algorithms, the domain of application of the systems they work on, and the integration of user-friendly interfaces for the final users. This expertise, which is in short supply and consequently a training challenge, is essential to mitigate risks associated with poor data quality, the outcomes derived from its analysis, and the societal digital gap. In this latter scenario, initiatives such as the Large-scale Skills Partnership on the 'Digitalisation of the Energy System' can support the achievement of such a goal.

Standards and recommended practices are also vital for risk management and to enable controlled technology adoption to allow industries to progress by building trust and efficiency. In this sense, DNV has invested extensively since 2021 to develop recommended practices providing guidance for organisations and industries including energy throughout the digitalisation journey (see DNV-RP-0671 'AI-enabled systems assurance' for a deeper detail).

Regulatory and trust issues may mean a few high-risk applications of AI in the energy industry in the short term. However, it is likely that the next two to five years will bring accelerated deployment of AI in smart grid monitoring and management, enhancing energy production, efficiency and reliability. AI-driven predictive maintenance in renewable energy installations such as wind and solar farms will become more prevalent, reducing downtime and optimising energy production.

In addition, AI applications in demand-response systems will become more sophisticated, enabling better balancing of energy supply and demand in an almost fully sensorised environment.

In conclusion, in the energy sector, the progression from analog to digitalisation, then machine learning and deep learning, and now generative AI, is a continuous, incremental journey. It will certainly make some use of generative AI for some technical and sales purposes probably, but is more focused on machine and deep learning in an industrial operations context for the near future. On the other side, the AI race is now totally different, with new processors to come and new algorithms to be more efficient. Even when the dependence on the computing resources remain, the possibility of dramatically reducing the exploitation of huge farms of GPUs for obtaining valid results can positively impact Europe, which traditionally has provided very good software solutions rather than hardware ones. This fact does not mean that the building of new processors could be forgotten, but the landscape of relying on new algorithm advances for integrating AI solutions in the energy sector under a human-centric approach should be strongly supported.

References

Agostinelli, S.; Cumo, F.; Guidi, G.; Tomazzoli, C. Cyber-Physical Systems Improving Building Energy Management: Digital Twin and Artificial Intelligence. Energies 2021, 14, 2338.

Ahmad, T., et al. Artificial intelligence in sustainable energy industry: Status Quo, Challenges and opportunities, Journal of Cleaner Production, Volume 289, 2021, 125834, ISSN 0959-6526, https://doi.org/10.1016/j.jclepro.2021.125834.

Ahmad, T., Zhang, D., Huang, C., Zhang, H., Dai, N., Song, Y., & Chen, H. (2021). Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production, 289, 125834.

Alabi, T.M. et al. A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems, 2022, Renewable Energy, 194, pp. 822 - 849, DOI: 10.1016/j.renene.2022.05.123.

Alan Turing Institute, https://www.turing.ac.uk/research/research-projects/trustworthy-and-ethical-assurance-digital-twins-tea-dt

Alipour, M., Salim, H., Stewart, R. A., & Sahin, O. (2021). Residential solar photovoltaic adoption behaviour: End-to-end review of theories, methods and approaches. Renewable Energy, 170, 471-486.

Alves, J., Lima, T. M., & Gaspar, P. D. (2023). Is industry 5.0 a human-centred approach? a systematic review. Processes, 11(1), 193.

Amoresano A., Langella G., Iodice P., and Quaremba G. 2023, Pattern recognition of two-phase liquid-gas flow by discriminant analysis applied to accelerometric signals, Physics of Fluids, 35.

Amos, B., Kolter, J. Z. (2017, July). Optnet: Differentiable optimization as a layer in neural networks. In International conference on machine learning. 34th International Conference on Machine Learning, PMLR 70:136-145

Andrae, A.S. Projecting the chiaroscuro of the electricity use of communication and computing from 2018 to 2030. Preprint. 504 2019:1-23.

Andrae, A.S., Edler, T. On global electricity usage of communication technology: trends to 2030. Challenges. 2015 Jun;6(1):117-57.

Anstine, D.M., Olexandr I. (2023), Machine Learning Interatomic Potentials and Long-Range Physics, The Journal of Physical Chemistry A, 127(11) 2417-2431. https://doi.org/10.1021/acs.jpca.2c06778

Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., ... & Wattam, S. (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. Renewable and Sustainable Energy Reviews, 130, 109899.

Aspuru-Guzik, A., Persson, K. 2018. Materials Acceleration Platform: Accelerating Advanced Energy Materials Discovery by Integrating High-Throughput Methods and Artificial Intelligence. Mission Innovation: Innovation Challenge 6. http://nrs.harvard.edu/urn-3:HUL.InstRepos:35164974

Azad, M. M., Kim, S., Cheon, Y.B., Kim, H.S. (2023). Intelligent structural health monitoring of composite structures using machine learning, deep learning, and transfer learning: a review. Advanced Composite Materials, 33(2), 162-188. https://doi.org/10.1080/09243046.2023.2215474

Batstone DJ, Keller J, Angelidaki I, Kalyuzhnyi SV, Pavlostathis SG, Rozzi A, Sanders WT, Siegrist H, Vavilin VA. The IWA Anaerobic Digestion Model No 1 (ADM1). Water Sci Technol. 2002;45(10):65-73. PMID: 12188579.

Battaglia, P.W., Hamrick, J.B., Bapst, V., Sanchez-Gonzalez, A., Zambaldi, V., Malinowski, Z., Tacchetti, A. "Relational inductive biases, deep learning, and graph networks." arXiv preprint arXiv:1806.01261 (2018).

Bennett, S., Spencer, T. "How will artificial intelligence transform energy innovation?". IEA report, https://www.iea.org/commentaries/how-will-artificial-intelligence-transform-energy-innovation

Bessa, R. J., Möhrlen, C., Fundel, V., Siefert, M., Browell, J., Haglund El Gaidi, S., et al. (2017). Towards improved understanding of the applicability of uncertainty forecasts in the electric power industry. Energies, 10(9), 1402.

Bessa, R.J., Lobo, Francisco S., Fernandes, Francisco S., Silva, Bernardo (2024). Data augmented rule-based expert system to control a hybrid storage system. IEEE MELECON 2024, Porto, Portugal.

Bhandari, U., Chen, Y., Ding, H., Zeng, C., Emanet, S., Gradl, P.R., Guo, S. (2023), Machine-Learning-Based Thermal Conductivity Prediction for Additively Manufactured Alloys, Journal of Manufacturing and Materials Processing 7, no. 5: 160. https://doi.org/10.3390/jmmp7050160

Bharadwaja, B.V.S.S., Nabian, M.A., Sharma, B. Physics-Informed Machine Learning and Uncertainty Quantification for Mechanics of Heterogeneous Materials. Integr Mater Manuf Innov 11, 607–627 (2022). https://doi.org/10.1007/s40192-022-00283-2

Bhuyan, B. P., Ramdane-Cherif, A., Tomar, R., Singh, T. P. (2024). Neuro-symbolic artificial intelligence: a survey. Neural Computing and Applications, 1-36.

Boobalan, S., Kalai Lakshmi, T.R., Ghate, S.N., Haqqani, M.H., Jaiswal, S. (2023), Enhancing Power Efficiency in 4IR Solar Plants through AI-Powered Energy Optimization, Engineering Proceedings 59, no. 1: 87. https://doi.org/10.3390/engproc2023059087

Bordin, C., Skjelbred, H.I., Kong, J., Yang, Z. Machine Learning for Hydropower Scheduling: State of the Art and Future Research Directions, Procedia Computer Science, Volume 176, 2020, Pages 1659-1668, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2020.09.190.

Browell, J., Haglund, S., Kälvegren, H., Simioni, E., Bessa, R.J., Wang, Y., van der Meer, D., (2023). Hybrid energy forecasting and trading competition. IEEE Dataport, doi: https://dx.doi.org/10.21227/5hn0-8091

Cao, Z. et al. Toward a systematic survey forcarbon neutral data centers," IEEE Communications 507 Surveys & Tutorials, vol. 24, no. 2, pp. 895–936, 2022.

Castin, N., Malerba, L. Calculation of proper energy barriers for atomistic kinetic Monte Carlo simulations on rigid lattice with chemical and strain field long-range effects using artificial neural networks, J. Chem. Phys. 132, 074507 (2010). https://doi.org/10.1063/1.3298990

Chang, M. et al. Trends in tools and approaches for modelling the energy transition, Applied Energy, Volume 290, 2021, 116731, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2021.116731.

Cheng, L., & Yu, T. (2019). A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems. International Journal of Energy Research, 43(6), 1928-1973.

Chinnici, M., Telesca, L., Mahfuzul, I., Georges, J.P. Scalable and Transparent Blockchain Multi-layer Approach for Smart Energy Communities. Lecture Notes in Networks and Systems Volume 595 LNNS, Pages 183 - 1972023 4th International Congress on Blockchain and Applications, BLOCKCHAIN 2022 L´Aquila13 July 2022 through 15 July 2022, ISBN 978-303121228-4, 2023

Christiano, P. F., Leike, J., Brown, T., Martic, M., Legg, S., Amodei, D. (2017). Deep reinforcement learning from human preferences. Advances in Neural Information Processing Systems, 30.

Ciccone, F., Bacciaglia, A., Ceruti, A., (2023), Optimization with artificial intelligence in additive manufacturing: a systematic review, Journal of the Brazilian Society of Mechanical Sciences and Engineering 45(6), 303. https://doi.org/10.1007/s40430-023-04200-2

Cremer, J.L., Kelly, A., Bessa, R.J., Subasic, M., Papadopoulos, P., Young, S., Sagar, A., Marot, A. (2024). A pioneering roadmap for ML-driven algorithmic advancements in electrical networks. IEEE ISGT Europe 2024.

Das, A., Kong, W., Sen, R., Zhou, Y. (2023). A decoder-only foundation model for time-series forecasting. arXiv preprint arXiv:2310.10688.

Das, A., Kong, W., Sen, R., Zhou, Y. (2023). A decoder-only foundation model for time-series forecasting. arXiv preprint arXiv:2310.10688.

Davis, Giabbanelli, Jetter (2019). The intersection of ABM and FCM: a review of an emerging hybrid modelling practice

De Chiara, D., Chinnici, M., Kor, A.L. Data mining for big dataset-related thermal analysis of high-performance computing (HPC) data center. Lecture Notes in Computer Science, Volume 12143 LNCS, Pages 367 – 38.

Deepseek-AI et al. (2024). DeepSeek-V3 Technical Report. arXiv preprint arXiv:2412.19437

Demaree, K., Athay, T. A., Cheung, K. W., Mansour, Y., Vaahedi, E., Chang, et al. (1994). An on-line dynamic security analysis system implementation. IEEE Transactions on Power Systems, 9(4), 1716-1722.

Desai, S.A., Mattheakis, M., Sondak, D., Protopapas, P., Roberts, S.J., Port-Hamiltonian neural networks for learning explicit time-dependent dynamical systems, Phys. Rev. E 104, 034312

DNV, https://www.dnv.com/news/dnv-launches-new-recommended-practices-for-safe-application-of-industrial-ai-248933/

DNV-RP-0671 Assurance of AI-enabled systems https://standards.dnv.com/explorer/document/5BDF814775DB435C8AF32242F73FCB71

Dong, X., Thanou, D., Toni, L., Bronstein, M., Frossard, P. (2020). Graph signal processing for machine learning: A review and new perspectives. IEEE Signal Processing Magazine, 37(6), 117-127.

Duchesne, L., Karangelos, E., Wehenkel, L. (2020). Recent developments in machine learning for energy systems reliability management. Proceedings of the IEEE, 108(9), 1656-1676.

E. M. de Oliveira and F. L. C. Oliveira, "Forecasting mid-long term electric energy consumption through bagging ARIMA and exponential smoothing methods," Energy, vol. 144, pp. 776-788, Feb. 2018.

Eidnes, S., Stasik, A.J., Sterud, C., Bøhn, E., Riemer-Sørensen, S., Pseudo-Hamiltonian neural networks with state-dependent external forces, Physica D: Nonlinear Phenomena, Volume 446, 2023, 133673, ISSN 0167-2789, https://doi.org/10.1016/j.physd.2023.133673.

Endsley, M. R. (2023). Ironies of artificial intelligence. Ergonomics, 66(11), 1656-1668.

Ferreño, D., Serrano, M., Kirk, M., Sainz-Aja, J.A. Prediction of the Transition-Temperature Shift Using Machine Learning Algorithms and the Plotter Database, Metals 2022, 12(2), 186. https://doi.org/10.3390/met12020186

Flores-Leonar, M.M., Mejía-Mendoza, L.M., Aguilar-Granda, A., Sanchez-Lengeling, B., Tribukait, H., Amador-Bedolla, C., Aspuru-Guzik, A. Materials Acceleration Platforms: On the way to autonomous experimentation, Current Opinion in Green and Sustainable Chemistry, Volume 25, 2020, 100370. https://doi.org/10.1016/j.cogsc.2020.100370.

Fox, J., Ela, E., Hobbs, B., Sharp, J., Novacheck, J., Motley, A., Bessa, R.J., et al. (2021). Forecasting and market design advances: Supporting an increasing share of renewable energy. IEEE Power and Energy Magazine, 19(6), 77-85.

Frangopoulos, C. A. (Ed.). (2009). Exergy, Energy System Analysis and Optimization-Volume III: Artificial Intelligence and Expert Systems in Energy Systems Analysis Sustainability Considerations in the Modeling of Energy Systems (Vol. 3). EOLSS Publications.

Fuertes, S., Picart, G., Tourneret, J.-Y., Chaari, L., Ferrari, A., Richard, C., 2016. Improving Spacecraft Health Monitoring with Automatic Anomaly Detection Techniques, in: SpaceOps 2016 Conference. American Institute of Aeronautics and Astronautics, Reston, Virginia. https://doi.org/10.2514/6.2016-2430

Gao, M., Zhou, S., Gu, W., Wu, Z., Hu, Z., Zhu, H., Liu, H. (2024). LFPLM: A general and flexible load forecasting framework based on pre-trained language model. arXiv preprint arXiv:2406.11336.

Gartner, J. Top 10 strategic technology trends for 2020. Stamford, CT, USA, 2019.[8] M. Uddin, Y. Darabidarabkhani, A. Shah and J. Memon, "Evaluating power efficient algorithms for efficiency and carbon emissions in cloud data centers: A review," in Renewable and Sustainable Energy Reviews, vol. 51, pp. 1553-1563, 2015.

Giglio E., Luzzani G., Terranova V., Trivigno G., Niccolai A., Grimaccia F., An Efficient Artificial Intelligence Energy Management System for Urban Building Integrating Photovoltaic and Storage, IEEE Access, 2023.

Gimelli, A., Mottola, F., Muccillo, M., Proto D., Amoresano A., Andreotti, A., Langella, G., Optimal configuration of modular cogeneration plants integrated by a battery energy storage system providing peak shaving service, Applied Energy, 2019, 242, pp. 974-993.

Greydanus, S., Dzamba, M., Yosinski, J. "Hamiltonian Neural Networks." Neural Information Processing Systems (2019).

Grishina, A. et al. A machine learning solution for data center thermal characteristics analysis. Energies, 13(17), ISSN: 19961073, DOI: 10.3390/en13174378, 2020.

Grishina, A. et al. Thermal Awareness to Enhance Data Center Energy Efficiency. Cleaner Engineering and Technology, V.16, https://doi.org/10.1016/j.clet.2022.100409, Feb 2022.

Gržanić, M., Capuder, T., Zhang, N., & Huang, W. (2022). Prosumers as active market participants: A systematic review of evolution of opportunities, models and challenges. Renewable and Sustainable Energy Reviews, 154, 111859.

Gupta, V., Choudhary, K., Mao, Y., Wang, K., Tavazza, F., Campbell, C., Liao, W,. Choudhary, A., Agrawal, A. MPpredictor: An Artificial Intelligence-Driven Web Tool for Composition-Based Material Property Prediction, Journal of Chemical Information and Modeling 63(7) 1865-1871. https://doi.org/10.1021/acs.jcim.3c00307

Hassabis, D., Kumaran, D., Summerfield, C., Botvinick, M. (2017). Neuroscience-inspired artificial intelligence. Neuron, 95(2), 245-258.

Higgins, A., Paevere, P., Gardner, J., & Quezada, G. (2012). Combining choice modelling and multi-criteria analysis for technology diffusion: An application to the uptake of electric vehicles. Technological Forecasting and Social Change, 79(8), 1399-1412.

Himeur, Y., Sayed, A., Alsalemi, A., Bensaali, F., Amira, A. (2023). Edge AI for Internet of Energy: Challenges and perspectives. Internet of Things, 101035.

Hoffmann, V., Torsæter, B.N., Rosenlund, G.H., Andresen, C.A. Lessons for Data-Driven Modelling from Harmonics in the Norwegian Grid. Algorithms 2022, 15(6), 188

Hua, W., Chen, Y., Qadrdan, M., Jiang, J., Sun, H., & Wu, J. (2022). Applications of blockchain and artificial intelligence technologies for enabling prosumers in smart grids: A review. Renewable and Sustainable Energy Reviews, 161, 112308.

Huang, J. A., Valette, A., Beaudoin, M., Morison, K., Moshref, A., Provencher, M., Sun, J. (2002, October). An intelligent system for advanced dynamic security assessment. In Proceedings. International Conference on Power System Technology (Vol. 1, pp. 220-224). IEEE

Hwang, T. (2018). Computational power and the social impact of artificial intelligence. arXiv preprint arXiv:1803.08971.

ISO/IEC JTC 1/SC 42 "Artificial Intelligence" committee page: https://www.iso.org/committee/6794475.html

Jin, M., Cao, P., Short, M.P., Predicting the onset of void swelling in irradiated metals with machine learning, Journal of Nuclear Materials, Volume 523, 2019, Pages 189-197.https://doi.org/10.1016/j.jnucmat.2019.05.054

Jones, N. et al. The information factories. Nature, vol. 561, no. 7722, pp.163–166,2018.

K. P. Amber, M. W. Aslam, S. K. Hussain. "Electricity consumption forecasting models for administration buildings of the U.K. higher education sector," Energy Buildings, vol. 90, pp. 127-136, Mar. 2015.

Kalra, P. K. (1988). Fault diagnosis for an HVDC system: A feasibility study of an expert system application. Electric Power Systems Research, 14(2), 83-89.

Karniadakis, G. E., Kevrekidis, I. G., Lu, L., Perdikaris, P., Wang, S., Yang, L. (2021). Physics-informed machine learning. Nature Reviews Physics, 3(6), 422-440.

Karpatne, A. et al., "Theory-Guided Data Science: A New Paradigm for Scientific Discovery from Data," in IEEE Transactions on Knowledge and Data Engineering, vol. 29, no. 10, pp. 2318-2331, 1 Oct. 2017, doi: 10.1109/TKDE.2017.2720168

Kezunovic, M., Pinson, P., Obradovic, Z., Grijalva, S., Hong, T., Bessa, R. (2020). Big data analytics for future electricity grids. Electric Power Systems Research, 189, 106788.

Kostenko, W.P., Torok, J.G., Demetriou, D.W. IBM z15: Improved data center density and energy efficiency, new system packaging, and modeling, in IBM Journal of Research and Development, vol. 64, no. 5/6, pp. 16:1-16:10, Sep.-Nov. 2020.

Kotary, J., Fioretto, F., Van Hentenryck, P., Wilder, B. (2021). End-to-end constrained optimization learning: A survey. arXiv preprint arXiv:2103.16378.

Kreuzer, T., Papapetrou, P., Zdravkovic, J. Artificial intelligence in digital twins-A systematic literature review, Data & Knowledge Engineering, Volume 151, 2024, 102304. https://doi.org/10.1016/j.datak.2024.102304

Lagomarsino, M., van der Kam, M., Parra, D., & Hahnel, U. J. (2022). Do I need to charge right now? Tailored choice architecture design can increase preferences for electric vehicle smart charging. Energy Policy, 162, 112818.

Luccioni, A.S., Jernite, Y., Strubell, E. Power Hungry Processing: Watts Driving the Cost of AI Deployment? In: Procs. FAccT '24, June 03–06, 2024, Rio de Janeiro, Brazil. https://doi.org/10.1145/3630106.3658542

Machorro-Cano, I., Alor-Hernández, G., Paredes-Valverde, M. A., Rodríguez-Mazahua, L., Sánchez-Cervantes, J. L., & Olmedo-Aguirre, J. O. HEMS-IoT: A Big Data and Machine Learning-Based Smart Home System for Energy Saving. Energies, 13(5), 1097.2020.

Madan, S., Bollinger, K. E. (1997). Applications of artificial intelligence in power systems. Electric Power Systems Research, 41(2), 117-131.

Marot, A., Donnot, B., Dulac-Arnold, G., Kelly, A., O'Sullivan, A., Viebahn, J., et al. (2021, August). Learning to run a power network challenge: a retrospective analysis. In NeurIPS 2020 Competition and Demonstration Track (pp. 112-132). PMLR.

Marot, A., Kelly, A., Naglic, M., Barbesant, V., Cremer, J., Stefanov, A., Viebahn, J. (2022). Perspectives on future power system control centers for energy transition. Journal of Modern Power Systems and Clean Energy, 10(2), 328-344.

Mashhoodi, B., Stead, D., & van Timmeren, A. (2019). Spatial homogeneity and heterogeneity of energy poverty: a neglected dimension. Annals of GIS, 25(1), 19-31.

Mauky, E.; A model-based control concept for a demand-driven biogas production. Universität Rostock, 2018. https://doi.org/10.18453/rosdok_id00002443

Maulin Raval, Ph.D. Candidate, Shubhendu Bhardwaj, Aparna Aravelli, Jaya Dofe, Assistant, Hardik Gohel, Smart energy optimization for massive IoT using artificial intelligence, Internet of things, 2021.

McKinsey, 2023 https://www.mckinsey.com/capabilities/people-and-organizational-performance/our-insights/human-centered-ai-the-power-of-putting-people-first

Méndez, J. I., Ponce, P., Meier, A., Peffer, T., Mata, O., & Molina, A. (2023). Empower saving energy into smart communities using social products with a gamification structure for tailored Human–Machine Interfaces within smart homes. International Journal on Interactive Design and Manufacturing (IJIDeM), 17(3), 1363-1387.

Meola, A., Weinrich, S., 2023. Hybrid modelling of dynamic anaerobic digestion process in full-scale with LSTM NN and BMP measurements. ESANN 2023. https://doi.org/10.14428/esann/2023.ES2023-133.

Mussi, M., Losapio, G., Maria Metelli, A., Restelli, M., Bessa, R.J., et al. (2024). Position paper on AI for the operation of critical energy and mobility network infrastructures. AI4REALNET Deliverable D2.1.

N. Fumo and M. A. R. Biswas, "Regression analysis for prediction of residential energy consumption," Renew. Sustain. Energy Rev., vol. 47, pp. 332-343, Jul. 2015.

Nassif, A.B., Talib, M.A., Nasir, Q., Dakalbab, F.M., 2021. Machine Learning for Anomaly Detection: A Systematic Review. IEEE Access 9, 78658-78700. https://doi.org/10.1109/ACCESS.2021.3083060

Nti, I. K., Teimeh, M., Nyarko-Boateng, O., & Adekoya, A. F. (2020). Electricity load forecasting: a systematic review. Journal of Electrical Systems and Information Technology, 7, 1-19.

Oikonomou, E., Zimmermann, N., Davies, M., & Oreszczyn, T. (2022). Behavioural change as a domestic heat pump performance driver: insights on the influence of feedback systems from multiple case studies in the UK. Sustainability, 14(24), 16799.

Omitaomu, O. A., & Niu, H. (2021). Artificial intelligence techniques in smart grid: A survey. Smart Cities, 4(2), 548-568.

Paltrinieri, N., Comfort, L., Reniers, G., 2019. Learning about risk: Machine learning for risk assessment. Saf. Sci. 118, 475-486. https://doi.org/10.1016/j.ssci.2019.06.001

Piloto, L., Liguori, S., Madjiheurem, S., Zgubic, M., Lovett, S., Tomlinson, H., et al. (2024). CANOS: A fast and scalable neural AC-OPF solver robust to N-1 perturbations. arXiv preprint arXiv:2403.17660.

Pogmore, L., & Wheeler, B. (2023). The human side of transition–putting people at the heart of energy transformation so no-one gets left behind. The APPEA Journal, 63(2), S96-S100.

Polhill, J. G., Filatova, T., Schlüter, M., & Voinov, A. (2016). Modelling systemic change in coupled socio-environmental systems. Environmental Modelling & Software, 75, 318-332.

Primc, K., Slabe-Erker, R., & Majcen, B. (2019). Constructing energy poverty profiles for an effective energy policy. Energy Policy, 128, 727-734.

Pruvost, H., Wilde, A., Enge-Rosenblatt, O. (2023). Ontology-based expert system for automated monitoring of building energy systems. Journal of Computing in Civil Engineering, 37(1), 04022054.

Racanière, S., Weber, T., Reichert, D., Buesing, L., Guez, A., Jimenez Rezende, D., et al. (2017). Imagination-augmented agents for deep reinforcement learning. Advances in Neural Information Processing Systems, 30.

Raissi, M., Perdikaris, P., Karniadakis, G.E., Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations, Journal of Computational Physics, Volume 378, 2019, Pages 686-707, ISSN 0021-9991, https://doi.org/10.1016/j.jcp.2018.10.045, https://www.sciencedirect.com/science/article/pii/S0021999118307125

Raza MQ, Khosravi A. (2015) A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. Renew Sustain Energy Rev, 50: 1352-72. https://doi.org/10.1016/J.RSER.2015.04.065.

Saranya A., Subhashini R., A systematic review of Explainable Artificial Intelligence models and applications: Recent developments and future trends, Decision Analytics Journal, Volume 7, 2023, 100230, ISSN 2772-6622, https://doi.org/10.1016/j.dajour.2023.100230.

Satre-Meloy, A., Diakonova, M., & Grünewald, P. (2020). Cluster analysis and prediction of residential peak demand profiles using occupant activity data. Applied Energy, 260, 114246.

Seifner, P., Cvejoski, K., Sanchez, R. J. (2024). Foundational inference models for dynamical systems. arXiv preprint arXiv:2402.07594.

Shareef H, Ahmed MS, Mohamed A, Al Hassan E. (2018) Review on home energy management system considering demand responses, smart technologies, and intelligent controllers. IEEE Access, 6: 24498-509. https://doi.org/10.1109/

Shaw, W. J., Berg, L. K., Cline, J., Draxl, C., Djalalova, I., Grimit, E. P., et al. (2019). The second wind forecast improvement project (wfip2): general overview. Bulletin of the American Meteorological Society, 100(9), 1687-1699.

Sheikh-Mohamed, Y.B. et al. "Graph Convolutional Networks for probabilistic power system operational planning," 2023 IEEE Belgrade PowerTech, Belgrade, Serbia, 2023, pp. 1-6, doi: 10.1109/PowerTech55446.2023.10202799.

Shrouf F., Miragliotta G., Energy management based on Internet of Things: practices and framework for adoption in production management. Journal of Cleaner Production, 2015.

Silver, D., Schrittwieser, J., Simonyan, K., Antonoglou, I., Huang, A., Guez, A., et al. (2017). Mastering the game of go without human knowledge. nature, 550(7676), 354-359.

Song, Y., Wang, T., Cai, P., Mondal, S.K., Sahoo, J.P. (2023), A Comprehensive Survey of Few-shot Learning: Evolution, Applications, Challenges, and Opportunities, ACM Comput. Surv. 55 (13), Article 271 (December 2023). https://doi.org/10.1145/3582688

Sovrano F, Sapienza S, Palmirani M, Vitali F. Metrics, Explainability and the European AI Act Proposal. J. 2022; 5(1):126-138. https://doi.org/10.3390/j5010010

Srivastava, S., Butler-Purry, K. L. (2006). Expert-system method for automatic reconfiguration for restoration of shipboard power systems. IEE Proceedings-Generation, Transmission and Distribution, 153(3), 253-260.

Stiasny, J., Chatzivasileiadis, S. (2023). Physics-informed neural networks for time-domain simulations: Accuracy, computational cost, and flexibility. Electric Power Systems Research, 224, 109748.

Suganthi, L., Iniyan, S., & Samuel, A. A. (2015). Applications of progra logic in renewable energy systems–a review. Renewable and sustainable energy reviews, 48, 585-607.

Sunal, C.E., Dyo, V., Velisavljevic, V., 2022. Review of Machine Learning Based Fault Detection for Centrifugal Pump Induction Motors. IEEE Access 10, 71344-71355. https://doi.org/10.1109/ACCESS.2022.3187718

Tamascelli, N., Campari, A.,Parhizkar, T., Paltrinieri, N., 2024. Artificial Intelligence for safety and reliability: A descriptive, bibliometric and interpretative review on machine learning, Journal of Loss Prevention in the Process Industries, 90, 105343. https://doi.org/10.1016/j.jlp.2024.105343.

Tamascelli, N., Paltrinieri, N., Cozzani, V., 2023. Learning From Major Accidents: A Meta-Learning Perspective. Saf. Sci. 158, 105984. https://doi.org/10.1016/j.ssci.2022.105984

Tanveer Ahmad , Dongdong Zhang , Chao Huang, Hongcai Zhang , Ningyi Dai, Yonghua Song, Huanxin Chen. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. Journal of Cleaner Production, 2021.

Tao, F.; Sui, F.; Liu, A.; Qi, Q.; Zhang, M.; Song, B.; Guo, Z.; Lu, S.; Nee, A. Digital twin-driven product design framework. Int. J. Prod. Res. 2019, 57, 3935-3953.

Teso, S., & Kersting, K. (2019, January). Explanatory interactive machine learning. In Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society (pp. 239-245).

Vafamehr, A., Khodayar, M.E. Energy-aware cloud computing. The Electricity Journal. 2018 Mar 1;31(2):40-9.

Vähäkuopus, S., Paananen, H., Anttila, L., Kupila, T. (2019). Predicting the impacts of the major disturbances for better resource management and situational awareness. 25th International Conference on Electricity Distribution (CIRED 2019)

Vale, Z. A., Moura, A. M. (1993). An expert system with temporal reasoning for alarm processing in power system control centers. IEEE Transactions on Power Systems, 8(3), 1307-1314.

Wagner, J., Berger, C.G., Du, X., Stubhan, T., Hauch, J.A., Brabec, C.J. (2021), The evolution of Materials Acceleration Platforms: toward the laboratory of the future with AMANDA, Journal of Materials Science, 56(29), 16422-16446. https://doi.org/10.1007/s10853-021-06281-7

Walke, Fabian; Bennek, Lars; and Winkler, Till J., "Artificial Intelligence Explainability Requirements of the AI Act and Metrics for Measuring Compliance" (2023). Wirtschaftsinformatik 2023 Proceedings. 77. https://aisel.aisnet.org/wi2023/77

Wang, B., Wang, J., Dong, K., Nepal, R. How does artificial intelligence affect high-quality energy development? Achieving a clean energy transition society. Energy Policy 2024, 186, 114010

Wilkinson, M., Dumontier, M., Aalbersberg, I. et al. The FAIR Guiding Principles for scientific data management and stewardship. Sci Data 3, 160018 (2016). https://doi.org/10.1038/sdata.2016.18

Williams, Z., https://arxiv.org/abs/2301.12011

Xin Liu; Liviu Ivanescu; Rui Kang; Martin Maier, Real-time household load priority scheduling algorithm based on prediction of renewable source availability",Vol. 58, 318-326, July 2012.

Xu, Z., Saleh, J.H., 2021. Machine learning for reliability engineering and safety applications: Review of current status and future opportunities. Reliab. Eng. Syst. Saf. 211, 107530. https://doi.org/10.1016/j.ress.2021.107530

Y. Liu, H. Chen, L. Zhang, X. Wu, and X.-J. Wang, "Energy consumption prediction and diagnosis of public buildings based on support vector machine learning: A case study in China," J. Cleaner Prod., vol. 272, Nov. 2020, Art. no. 122542.

Yang, N., Yang, C., Wu, L., Shen, X., Jia, J., Li, Z., et al. (2022). Intelligent data-driven decision-making method for dynamic multisequence: An E-seq2seq-based SCUC expert system. IEEE Transactions on Industrial Informatics, 18(5), 3126-3137.

Ye, Y., Qiu, D., Sun, M., Papadaskalopoulos, D., & Strbac, G. (2019). Deep reinforcement learning for strategic bidding in electricity markets. IEEE Transactions on Smart Grid, 11(2), 1343-1355.

Yu, J., Zhao, Y., Pan, R., Zhou, X., Wei, Z. (2023), Prediction of the Critical Temperature of Superconductors Based on Two-Layer Feature Selection and the Optuna-Stacking Ensemble Learning Model, ACS Omega 8(3), 3078-3090. https://doi.org/10.1021/acsomega.2c06324

Zawadzki, P; Lin, Y; Dahlquist, F; Bao, T; Laurain, A-L; Johnson, K. (2016). Personalized energy efficiency program targeting with association rule mining. ACEEE Summer Study on Energy Efficiency in Buildings.

Zhang, Z. Z., Hope, G. S., Malik, O. P. (1989). Expert systems in electric power systems - a bibliographical survey. IEEE Transactions on Power Systems, 4(4), 1355-1362.

Zhou, S., Hu, Z., Gu, W., Jiang, M., & Zhang, X. P. (2019). Artificial intelligence based smart energy community management: A reinforcement learning approach. CSEE Journal of Power and Energy Systems, 5(1), 1-10.

Zhu, X., Li, x., Zheng, M. (2022). Predicting the Irradiation Swelling of Austenitic and Ferritic/Martensitic Steels, Based on the Coupled Model of Machine Learning and Rate Theory, Metals 12, no. 4: 651. https://doi.org/10.3390/met12040651

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