UK Parliament POST

POSTnote 735

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10 December 2024

Energy security and AI

Overview

- Artificial intelligence (AI) and machine learning have a range of current and emerging applications within the energy sector, with the potential to optimise and accelerate energy planning, generation, and use.
- AI could use data from devices such as smart meters and substation monitoring to help address current regional renewable connection delays and excessive network congestion. It could also speed-up decarbonisation of the energy system as the UK strives to meet 2030 grid decarbonisation, 2050 Net Zero targets and reduce costs for consumers.
- There are technical and infrastructural barriers to wider adoption of AI in the energy system, including data access, regulation, skills gaps, and availability and reliability of the physical infrastructure that supports AI.
- Stakeholders have raised concerns around privacy, cyber security, energy use, fairness, ethical use, and operational challenges.
- Stakeholders suggest that more support is needed to develop AI in the sector, and that regulation needs to change to ensure optimal benefits can be gained from wider integration of AI in the energy system, while avoiding potential risks.

Background

Global intergovernmental organisations suggest that artificial intelligence (AI) and machine learning (ML) could play a significant role in addressing energy system limitations and the transition to Net Zero.[1–3]

The UK Government has committed to decarbonising the national electricity grid by 2030 under the Department of Energy and Net Zero Mission Control initiative,[4,5] pulling the previous target forward by five years,[6] which largely requires increasing electricity generation from renewable sources.

The use of AI has the potential to reduce strain on the network and speed-up renewable connections as the UK works to meet its Net Zero targets, while also reducing costs from the operator to the consumer.[7,8]

The UK grid is facing regional renewable connection delays, with green energy projects facing waiting times of 10 to 15 years[9,10] and 63% of projects in the pipeline not changing development status between 2018 and 2023.[11] The network is also limited by capacity bottlenecks driven by excessive network congestion and aging infrastructure.[12] The queue[a] for renewable connection sits at over 700GW according to Energy UK and Ofgem, with estimates this could rise to 800GW by the end of 2024.[19,20] This is four times more than predicted capacity needs by 2050.[21,22,23]

At present, to maintain network stability and manage network constraints caused by maintenance outages or network limitations the National Energy System Operator (NESO) pays constraint payments to energy generators such as gas power stations and renewable energy generators to turn up or turn down their output. In the 2023/2024 financial year, constraint costs were £1.6 billion, making up around 65% of overall balancing costs and roughly 2% of a consumer electricity bill. NESO forecasts that in the next five years this could exceed £3 billion annually.[12]

Greenbyte AB, a renewable energy management platform, estimate that the world's wind turbines generate more than 400 billion points of data annually, data which could be used to better understand turbine performance.[13] There is potential for AI and ML technologies to leverage this type of big data to improve the efficiency of energy generation, storage and use.[14,15]

However, there are uncertainties around the use of AI tools, with some stakeholders expressing concerns over privacy, security, transparency, and ethical use.

This note will explain the current and emerging applications of AI and ML in the energy system; barriers to wider implementation; the challenges likely to be encountered; and policy considerations proposed by stakeholders.

[a] The process for new connections (including renewable energy generators) involves an optional pre-application process and formal application process.[16] While projects await connection after going through the formal application process they remain in a queue and are rarely withdrawn, meaning other projects that are ready to go can be blocked.[17] In November 2023 Ofgem announced new queue management process measures to remove stalled projects from the queue.[18]

What is AI in the context of energy security?

AI and ML

AI does not currently have a universally agreed definition.[24] The UK Government's 2023 policy paper defines AI as "products or services" that are "adaptable" and "autonomous".[25] ML is a subset of AI that is capable of learning by finding patterns in data, before applying these findings to make predictions or generate outputs (PB 57).[26] ML can be split into two distinct classes, generative and predictive: [27]

- Generative AI is used to create new content, such as ChatGPT.[28,29]
- Predictive AI is used to forecast patterns and identify future trends based on existing data.[30]

Industry stakeholders indicate that predictive AI will provide key benefits to the energy system. In all cases, access to data is required for training the AI model (PB 57).

Energy security

There is no agreed definition for energy security,[31] though the definition set out by the International Energy Agency (IEA) of "the uninterrupted availability of energy at an affordable price" is commonly used (PN 676).[32]

AI is already being developed and used in the UK grid, predominantly by the national transmission network and energy system operators[b] for forecasting and maintenance.[37–40]

Wider implementation of AI and ML in the energy system could optimise energy planning, generation and use.[32] Ofgem suggest that benefits will apply across the value chain, from operators through to consumers. Academic stakeholders expect improved efficiency to allow lower cost energy for consumers and increased capacity to balance the grid to reduce or delay the need for large infrastructure investments.

However, industry stakeholders note that investment in physical grid infrastructure is critical to ensuring long-term energy security of the UK. AI could help to increase the number of renewable generators connected to the network, which could accelerate the transition towards a decarbonised grid and Net Zero targets.[8,41]

[b] The National Energy System Operator (NESO) oversees and operates the electricity system, balancing supply and demand.[33] National Grid manages the high-voltage national transmission network, transporting electricity from generators and interconnectors.[34] Distribution Network Operators (DNOs) own and operate regional systems of cables and towers, and are licensed to distribute electricity to suppliers.[35,36]

Applications of AI and ML in the energy sector

AI and ML have a range of existing and possible uses within the energy sector, from network scale operations to consumer level:

Table 1: Applications of AI and ML in the energy sector

Application	Explanation	Impact
Improved forecasting of renewable energy	Renewable energy generation, such as wind and solar photovoltaic (PV), is inherently intermittent (PN 464).[42] AI models can predict energy generation using weather patterns and historical outputs, continually learning to produce incrementally more accurate predictions on the amount of energy that will be available from these sources.[43–45]	NESO in collaboration with the Alan Turing Institute reported a 33% improvement in solar forecasting with the use of AI, which helps reduce the cost of running the grid.[46]
Optimised efficiency of renewable energy generation	AI can be deployed to wind turbines and solar panels, adapting to changing conditions in real-time to, for example, adjust the orientation and tilt of solar panels,[47,48] or the pitch and yaw of wind turbine blades to maximise output.[49]	The New Scientist reported that the uptake of AI in wind turbines globally would improve efficiency by 0.3%, enough extra energy to power a moderately sized country.[50]
Improved energy load forecasting	AI utilises historical data and information from smart devices on consumer behaviour to predict expected energy demand. The ability of AI to process real-time data allows forecasts to be continually updated, improving accuracy.[40,51] AI can identify complex patterns of usage where demand is volatile, that traditional forecasting methods would be unable to capture.[52,53]	More precise estimations of peak usage times enable easier balancing of supply to the network.[53] Short-term load forecasting with AI has consistently demonstrated 95% accuracy or higher.[54]
Predictive maintenance	Tracking the health status of physical assets, such as sensors monitoring the thermal condition of transmission cables or remote inspection of offshore wind farms.[53] Using AI to proactively identify potential equipment failures before they occur could minimise downtime, increase asset lifespan and reduce costs.[75,76]	According to a report across 268 companies by PWC, predictive maintenance can extend asset lifetime by 20% and decrease maintenance costs by 12%.[77]

Energy storage optimisation	Batteries are important for maintaining a consistent energy supply in the grid, especially with increasing renewable generation.[62,63] AI can predict optimum times for charging and discharging.[64] By monitoring battery degradation AI may help to extend the lifespan of energy storage systems.[65]	Use of an AI model demonstrated a 4.6% reduction in capacity decay rate after 3300 charging and discharging cycles.[66]
Cyber security	As the energy system becomes more digitalised there is an increased risk of cyber-attacks. AI can continuously monitor network activity to assist in detecting and responding to cyber security threats in real-time.[53,73]	A 2024 report of 604 organisations from the Ponemon Institute found that organisations using AI to automate cyber security saved on average US $1.88 million and shortened breach containment lifecycle by 108 days.[74]
Market design and operation	As the energy market becomes more decentralised with distributed local renewable energy production, the energy market will become more complex.[53] According to research organisation RAND, AI could optimise the market by managing microgrids[c], localised pricing and peer-to-peer trading with automated real-time pricing.[40]	The use of AI in energy markets could disrupt the current centralised wholesale approach.[79] This should, in theory, lower costs for the consumer.
Project planning	AI can be used to identify optimal locations for new renewable energy projects.[91] Using AI-powered drones to perform aerial surveys and land mapping, or analysing weather patterns while accounting for environmental regulations to expedite the planning and deployment of renewable energy connections.[91,92]	According to Offshore Renewable Energy (ORE) Catapult, innovative technologies like AI have the potential to reduce consenting timelines from five to three years, a time saving of 40%.[93]
Data gap filling	Sensor coverage does not penetrate all areas and generators producing less than the 1MW threshold do not need to be registered.[83,84] For accurate predictions this energy use and generation needs to be accounted for. AI could be used to model fragmented, inconsistent or missing data.[53]	ML algorithms outperform standard models in estimating missing solar energy generation data.[85]

[c] Microgrids are small-scale, controllable energy grids serving a localised area such as a university campus.[86,87] They are connected to the main grid but can be self-contained and operate independently to protect the local network.[87,88]

Data extraction and integration	Large amounts of historical energy data are still held as physical records. AI could automate the digitisation of such records, allowing their use in future predictions.[78] Distribution network operators (DNOs) currently run independent systems with different types of metering.[79] AI could assist in making these datasets more interoperable.[80]	UK Power Networks partnered with Google Deepmind to use image recognition software to digitise hand-drawn electricity cable maps spanning over 180,000km.[81] The use of AI cut 20,000 hours of manual scanning work down to 15 minutes.[82]
Benchmarking	AI could identify cases of suspected energy theft by measuring electricity demand from properties and benchmarking expected usage patterns to recognise anomalies.[67,68]	A 2021 study across 138 countries by the Northeast group found that electricity theft and non-technical losses cost utilities US $101.2 billion per year in lost revenue.[69] Several AI energy theft identification models have been put forward, with reported detection rates ranging from 93-94% and false-positive rates of 1.1-11%.[70–72]
Smart grid management and demand side response	AI functions in the automation of smart grids, comprising of advanced monitoring with two-way communication to detect and respond to energy usage in real-time.[55,56] Through control of smart and Internet of Things (IoT)[d] devices, AI can adjust electricity consumption to match available supply (PN 715).	US utility company Florida Power and Light utilised smart meter data to optimise grid management, saving US $30 million in operational costs in 2014.[58] According to Juniper research, smart grids are forecasted to save US $291 billion in global energy costs by 2029.[59] The Amsterdam City-Zen smart grid retrofitting project achieved an estimated annual reduction of 35,000 tonnes of CO_2 emissions.[60,61]
Automated frequency control	The power grid must maintain power flows between acceptable frequency ranges at all times to ensure stability.[89] The calculations are computationally demanding and often have to be simplified to obtain rapid solution.[41] AI can automate this process, learning optimal solutions and accelerating solutions.[41,90]	No current instance / example of measurable impact.

[d] The Internet of Things (IoT) refers to the network of physical devices that are embedded with sensors and network connectivity, capable of collecting and sharing data, such as smart meters, electric vehicles and other smart appliances.[57]

Impacts on energy systems

Potential barriers

There are a range of factors that currently pose a barrier to the adoption and deployment of AI more widely within the energy sector, which can broadly be divided into technical and infrastructure barriers.

Technical barriers

Explainability

High performance AI models are generally complex, so decision-making processes can be complex.[40,94] This is often referred to as 'black-box AI'[e], where it can be difficult to understand and explain how an AI model decided on a certain outcome (PN 633).[95]

The electricity system is classified as a Critical National Infrastructure[f], so the ability to trace the chain of decision making is of particular importance.[97] The lack of explainability around the decisions taken by AI has impacted stakeholder confidence and slowed uptake within the energy sector.[98] Advances in explainable AI are important to support deployment of applications as the energy system transitions to decarbonisation.[41]

Culture

The IEA suggests that the energy industry is traditionally resistant to rapid change and has a relatively conservative management culture.[1] Stakeholders suggest that while risk averse planning is done with the right intentions, this mindset acts as a blocker to innovation. According to classification society Det Norske Veritas (DNV), navigating resistance to change will be crucial in unlocking the full capacity of AI in the energy sector.[99]

Data access

The quality of an AI model is dependent on the quality and volume of data on which it is trained (PB 57).[100] Smart meter data is considered as personally identifiable under GDPR and access is governed by Data Access and Privacy Framework (DAPF).[101] Smart meter data is currently mainly limited to energy suppliers and Distribution Network Operators (DNOs).[102] Many of the datasets are siloed due to commercial sensitivity or regional inconsistencies in DNO data privacy policy making it unclear what data can be shared.[79] However, aggregated smart meter data is now

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[e] Black box AI refers to AI systems with internal decision-making processes that are not transparent.[95] While inputs and outputs can be understood, the systems powering the model may be so complex that they are uninterpretable to humans.[95]

[f] Critical National Infrastructure refers to "assets, facilities, systems, networks or processes and the essential workers that operate them", the loss or compromise of which could lead to "Major detrimental impact on the availability, integrity or delivery of essential services", including those that could "result in significant loss of life or casualties" or "significantly impact national security, national defence, or the functioning of the state".[96]

classified as open energy system data with DNOs required to publish aggregated consumption data.[103,104]

Stakeholders identified access to data, especially granular data, as a limiting factor for innovators in this area. In July 2024 Ofgem released a consultation on the governance of data sharing infrastructure, with the intention of driving greater availability and standardisation of data.[105] NESO is currently developing 'Data Sharing Infrastructure', formerly the 'Digital Spine'[g], where it will act as the single coordinator allowing access to relevant data for certain stakeholders.[108]

Jobs and skills

The UK is facing a skills gap in personnel with energy sector knowledge and digital literacy (PN 697).[109] A 2023 survey by Energy Systems Catapult found that 40% of businesses in the energy sector found it difficult to hire data scientists with the necessary skills.[110] A survey of 604 organisations across 16 countries, conducted by IBM and Ponemon Institute, reported that the cyber skills gap has grown by 26.2% between 2023 and 2024.[74] There is a suggestion that AI may have a role in addressing the energy sector knowledge skills gap, by combining energy industry knowledge that is often fragmented and accessible only to specialists.[111]

Industry stakeholders point to the need to make positions within energy more competitive to attract the necessary AI talent, and workforce upskilling initiatives.[112] According to a survey conducted by Microsoft, Masdar and the Abu Dhabi National Oil Company (ADNOC), 78% of business leaders consider talent and training a challenge in adoption of AI.[113]

Regulation

The IEA states that "government policies and regulations will play an important role in the deployment of digital technologies", recommending that regulators consider removing older regulations and introduce new statutes.[1] Industry stakeholders suggest that the established benefit-measuring metrics that drive decision making, funding and bring together industry and government may not fully capture the benefits of AI and developing technologies.[114–116]

Academic and industry stakeholders note AI technologies are rapidly advancing, and existing regulatory frameworks may not keep pace, so it is important for regulators to stay up to date with the latest developments.[40]

There are calls from stakeholders to adapt regulatory frameworks to facilitate a supportive environment for innovation, providing incentives encouraging investment in AI development, while ensuring privacy, security and ethical use.[92] Changes to policy and regulation will likely be critical in ensuring the digital transformation of energy is fully realised and to accelerating decarbonisation.[1,41]

[g] The Digital Spine refers to the data sharing infrastructure plans for the energy system, with a set of rules, processes and technical functions aimed at facilitating secure data exchange for organisation within the energy sector.[106,107]

Infrastructure barriers

Communication infrastructure

Communication is central to the real-time operation of power systems as envisioned with smart grids.[117] Distributed edge devices[h] need contact with each other, the main server and low latency[i].[122,123]

However, older power system infrastructure is not thought, by some stakeholders, to be equipped to handle the demands of emerging technologies.[124] A 2022 report from the Energy Digitalisation Taskforce noted the need to improve interoperability[125,126] and recommended updating standards to ensure smart devices are able to communicate with one another. Upfront costs required to upgrade software and hardware necessary for AI integration can be prohibitive.[91]

Stakeholders note that for digitalisation of the energy network, greater coupling is needed between areas the energy system is dependent on, such as the communication network. They suggest co-planning and co-locating infrastructure is required for a productive outcome.

Computing power

AI is reliant on substantial computing power to train, tune and deploy models.[127] Large-scale models, in particular, require on average 100 times more computing power than other contemporary AI models.[128,129]

Intergovernmental stakeholders such as the Organisation for Economic Co-operation and Development (OECD) suggest that sufficient computing power is an important component in expanding integration of AI in the energy system.[130]

Others suggest it will be necessary to address connection bottlenecks and environmental concerns surrounding the scalability of data centres that provide these computing services (Box 1).[131–133]

Box 1: Data centres

AI requires physical infrastructure to support its operations and is energy intensive to train and maintain (PN 677), something stakeholders suggest is often overlooked. According to Statista, as of March 2024 the UK had 514 data centres, the third most globally.[134] Data centres are now designated as "Critical National Infrastructure".[135] Data centres accounted for almost a fifth of all electricity usage in the Republic of Ireland in 2022, an increase of 400% since 2015.[136] Morgan Stanley predicts that the power demand from generative AI will increase at an average of 70% per year over the next three years, largely driven by the growth of

[h] Edge devices are computing devices that operate on the edge of the network, such as sensors and actuators.[118] They may be capable of collecting and transmitting data, or hosting a local AI model, and so can be classified as part of the IoT.[118,119]

[i] Latency refers to the amount of delay in network communication.[120] A network with low-latency has faster response times.[121]

data centres, and by 2027 may use as much energy as Spain needed to power itself in 2022.[137]

Data centres also need to be temperature controlled to prevent overheating. Traditional approaches utilise air cooling. However, liquid cooling has received increasing attention as a thermodynamically efficient alternative.[138,139] Academic stakeholders have raised concerns about the efficiency of cooling with water and the possibility of burdening local resources,[140] especially as centres are generally clustered around major population centres.[141] Estimates from one study have global AI use accounting for between 4.2 and 6.6 billion cubic meters of water by 2027, which is equivalent to approximately two-thirds of England's current annual water consumption.[142,143] Cooling requirements account for 40% of data centre electricity demands.[144] Concerns over energy usage led to Ireland placing a hold on the development of new data centres in Dublin, effective from 2022 to 2028,[145] while a three-year moratorium was imposed in Singapore from 2019 to 2022,[146] and a similar restriction was implemented in Amsterdam from 2019 to 2020.[147,148]

Challenges for energy system AI use

Privacy and security risks

Academic stakeholders have raised concerns about data privacy and ownership (PB 57). According to research consortium EnergyREV, privacy was the most common concern raised by energy sector stakeholders.[149] Energy companies have access to large volumes of personal data, in some cases every half-hour.[40,102] This information could be used to determine socio-economic and demographic profiles, or insight into daily routines of a household.[40,102] This opens up the possibility of discriminative customer segmentation[j].[150] In the event of a data breach, properties may be at risk of robbery if patterns of unoccupancy can be inferred.[150]

The capacity for AI to extract granular information from overlapping datasets from IoT devices, and the unpredictability with which this information may be used by models, makes it difficult to inform data subjects about what insights are being made from their data.[150,151] A report from ADViCE highlights the need to balance the requirements for sufficient data access and preserving consumer privacy.[53] The smart Meter Implementation Programme (SMIP) has recognised that smart metering presents a significant privacy risk, and so instituted a DAPF, which sets out by whom, and how, data can be accessed.[102]

There are cyber security concerns regarding system operations. Legacy infrastructure designed before cyber security was a concern may expose vulnerabilities, and the globalised nature of asset supply chains makes it difficult to ensure products are procured from trusted sources (PN 554). Malicious actors, from individual hackers to national cyber-offensive programmes, may attempt to launch cyber-attacks on the electricity system, such as the first confirmed cyber-attack specifically against an

[j] Discriminative customer segmentation refers to practices that unfairly segment the customer base. For instance, the use of temporary offers to encourage users to share their data, which is subsequently used to identify high-peak time users and offer less favourable tariffs.[150]

electricity network in 2015 in Western Ukraine and subsequent attacks that cut off power to around 255,000 people.[1,152]

Increased use of digital technologies within the electricity system increases the cyber security risks, and the integration of distributed energy sources interconnected with digital systems increases exposure by providing more potential points of entry.[153,154] A spate of cyber-attacks in 2022 impacted German wind turbine operators,[155,156] the first of which interrupted remote monitoring of 5,800 wind turbines with 11GW of energy output.[157–159] AI applications may present the additional vulnerability of false data injection, where adversaries tamper with datasets to 'poison' models and interrupt correct functioning.[40]

Fairness and accessibility risks

Ensuring that the use of AI does not exacerbate existing inequalities was identified by intergovernmental stakeholders as a potential concern.[160] Sustainable Energy for All state that in "the AI sector, where the workforce is heavily male dominated…only 12% of positions requiring over 10 years of experience [are] held by women".[161,162] The lack of diversity in AI development teams could lead to technologies that reflect gender biases.[163]

AI models are shaped by the historical data used in their training (PB 57). There is a risk that underlying biases present in initial datasets could lead to unfair outcomes for protected characteristics.[164,165]

Smart devices are currently expensive and, though there is very little information on their demographic uptake, financial constraints consistently emerge as a barrier to their adoption.[166] Academic and NGO stakeholders suggest that due to imbalanced uptake of these devices based on income or region, data currently being generated may not accurately reflect wider energy use patterns,[167] and could potentially lead to AI optimisations that do not benefit digitally excluded consumers.

If AI applications are designed to obtain the optimal outcome economically, there are concerns that this could lead to unethical and biased decision-making.[40] For example, an AI model tasked with reducing peak electricity demand may decide to limit energy to inefficient homes, which are more likely to belong to already disadvantaged people.[40] Academic and regulatory stakeholders note that separate AI models reacting to the same signals may facilitate market manipulation, engaging in activities to make prices higher than they otherwise would be through tacit collusion[k].[40]

Technical and operational risks

With the 'black box' nature of some AI applications, and outsourcing of AI development to private companies, there is a risk that system operators would be using programmes they do not, and in instances cannot, fully understand, making human intervention difficult.[169] Academic stakeholders note the need for explainable and contestable AI, where dynamic human-machine interaction is used to explain and revise the decision making process, to ensure that AI powered decisions align with intended goals.[170] It is important to be able to diagnose faults and limit unpredictable

[k] Tacit collusion refers to algorithms engaging in automated strategies to track prices and introduce common policies to give market signals that optimise joint profits, without explicit collusion from the companies operating them.[168]

system behaviours that could lead to cascading effects that disrupt Critical National Infrastructure, such as the energy system.[40,53,171]

According to a 2023 World Economic Forum report, 23% of jobs globally may be disrupted by AI in the next 5 years (PN 708).[172] There are concerns that automation and advancements in AI could reduce the number of staff required in traditional roles within the energy sector, such as field technicians, maintenance staff and data analysts.[1,173–175]

Potential mitigation approaches

Privacy-preserving technologies

'Privacy preserving/enhancing' technologies can be used to maintain the security of sensitive personal information. For example, Federated Learning[l] has data kept locally, and the model is trained locally, with only parameters shared to central servers.[102] Homomorphic Encryption[m] allows operations to be performed on encrypted data without the need for decryption, ensuring the underlying data cannot be accessed.[178] These are just two examples of a range of possible techniques. However, these technologies are complex and may therefore use more energy.[102]

Enhanced cyber security and digital literacy

The EU AI Act sets out how to implement robust cyber security measures and investing in resilience to protect AI systems.[179,180] The US National Institute of Standards and Technology (NIST) released an updated framework for dealing with cyber security threats in 2024,[181] while the National Cyber Security Centre (NCSC) produced guidelines for secure AI system development in 2023.[182] The IEA suggests that digital energy security should be built around:[1]

- Resilience – the ability to withstand shocks and adapt quickly.
- Security by design – where security objectives are a core part of the design process.
- Cyber hygiene - with precautious access right allocation and training in digital literacy for staff.

Stakeholders state that adherence to frameworks such as these, and implementation of clear regulation, can help to reduce the cyber security risks associated with AI in the energy system.

AI could also play a role in proactive threat detection, in efforts to identify and mitigate cyber intrusions before they occur.[183,184] Microgrid electricity networks may

[l] Federated Learning is a distributed machine learning technique, using multiple servers to share model updates without exchanging raw data.[176]

[m] Homomorphic Encryption is a cryptographic approach that, unlike conventional encryption, allows information to be processed while it remains encrypted.[177]

benefit from being 'islanded', through temporary segregation from the rest of the network in the event an attack, to limit the scale of outages.[1]

Balanced model training and validation

Fair datasets hold the key to unbiased and equitable outcomes,[185] so it is important that the data used to train models is as representative as possible. Development of AI applications that are explainable and interpretable will contribute to improved accuracy, reliability and robustness, to limit potential biases and fairness concerns in models.[98,186]

Academic and NGO stakeholders suggest including humans in the training process. Interrogating decisions and contesting outputs could allow movement towards a 'grey box' model, with greater transparency of the whole process from design to deployment. The government recently announced an AI assurance platform, intended to increase trust by mitigating risks and drive adoption of responsible AI.[187]

A 2024 Deloitte risk management report recommends:[188]

- Certification on the adequacy, representativeness and quality of data used in AI training.
- Data cleansing and label checking to eliminate errors.
- Concrete and trustworthy demonstration from developers that systems adhere to ethical and legal standards.
- Thorough testing of models on diverse datasets for validation.
- Continuous performance tracking to ensure reliability and transparency are maintained.

Financial support

To realise the full potential of AI optimisation in the energy system, academic and industry stakeholders suggest clear regulations and incentives are needed to attract investment.[92] Investment from government and research funders in sector specific research for energy data and AI could create an ethics-conscious, pro-innovation culture.[149] Careful planning and significant investment in AI technologies could overcome the challenges of AI.[189]

In 2023, the government announced the Manchester Prize AI initiative, a multi-million pound and multi-year challenge, the second round of which is aimed at clean energy systems.[190–192]

Stakeholders highlighted the need for investment in making trust in AI happen, the creation of suitable sandboxes for innovation and subsidies to support the equitable implementation of AI-based energy solutions, to ensure underserved communities are not left behind in the energy transition.[189]

Standardised processes and ethical oversight

Clear protocols, regular re-evaluations and regulatory oversight could help move approaches beyond legal compliance towards ethical best practice.[149,184,193] The EU AI

Act calls for authorised auditors with access to algorithms, data, and the decision making process to assess regulatory compliance.[180]

Stakeholders suggest that there is an opportunity for the UK to establish itself as a global leader by setting 'gold-standard' best practice guidelines and ethical frameworks.

Stakeholders also note the importance of forward planning and the need to approach risks in a less siloed way. For instance, regulation of infrastructure surrounding AI such as green data centre hosting requirements or sustainability reporting schemes currently being explored and implemented by the European Commission.[194,195]

Impacts on energy systems and market approaches

As the grid becomes more distributed, with increased generation capacity and greater rates of digitisation (PN 655), AI could also help automate 'bidirectional markets'[n].[196] AI could manage complex interactions between local markets or microgrids, and rapidly react to granular market signals to facilitate dynamic real-time peer-to-peer trading.[79,197–200] Expansion of mechanisms such as demand side response (PN 715), coupled with small scale renewable generation, could transform end users from passive consumers to active participants in the energy system. The IEA has suggested that distributed generation developments could transform the way that electricity supply functions.[1]

Industry stakeholders suggest that while AI is a tool for optimising transition of the energy system, it is not the driver of these changes.[201–204] Some stakeholders also suggest that there will be very little impact in the next decade, as the current energy sector is not designed for rapid adaptive changes.

Policy considerations

Policy consideration	Explanation
Reframing energy and consumer engagement	• Rethink energy as a shared resource, promoting sustainable use and prioritising consumer transparency and engagement as active participants. • Understanding user perspectives and motivating technology adoption are important for a shared commitment to the energy transformation.
Cyber security and system resilience	• Cyber security updates and factoring in real-world disaster scenarios (such as flooding) could be important considerations

[n] Bidirectional energy markets allow power to flow both to and from the centralised energy system, enabling small, distributed energy generators to use energy from the grid when required, and sell energy to the grid when production is in excess.[196]

	given the critical nature of the electricity supply and interconnectedness with other Critical National Infrastructure. • Stakeholders noted that AI systems will need to be resilient and equipped for cyber defence with the ability to report attacks and factor in supply chain vulnerabilities in physical infrastructure.
Environmental and infrastructure considerations	• AI is an energy intensive product, and data centres that support it have a large environmental footprint. Stakeholders suggest regulation is needed, reducing the carbon footprint of data centres to align with sustainability and Net Zero targets.[205] • Investment in transmission networks and physical infrastructure would be needed to support AI-enhanced energy systems, while AI can optimise planning for these projects.
Governance, planning, and regulatory updates	• Stakeholders suggest that AI requires updated governance, long-term energy system planning, and incentives for data access. • Regularly updated standards, clear collaborative regulatory frameworks, and national energy plans would be important considerations ensuring the safe and responsible integration of AI.
Trust, transparency, and ethical standards	• Building trust in AI requires traceability, explainability, and privacy with a clear framework for contestable and transparent AI. • The UK has an opportunity to lead with ethical standards, transparency, and community engagement, ensuring AI assumptions are explainable to the public.
Investment in skills and capacity	• Investment in digital literacy, AI education, competitive job conditions (PN 697) and industry support to develop system capabilities will be important considerations. • Stakeholders suggest that AI hubs and local supply chains could strengthen energy sector resilience and innovation.
Role and responsible use	• AI is a supporting tool and not the solution in isolation. Responsible use with oversight, regulatory scrutiny, and measurable standards could maximise its positive impact. • Stakeholders suggest the focus should be on specific AI applications, such as forecasting and system optimisation to increase the rate of energy system decarbonisation and avoid over-reliance on supportive tools such as predictive maintenance.

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DOI: https://doi.org/10.58248/PN735

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