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Artificial intelligence: the strategic catalyst for a resilient and decarbonised energy future

Artificial intelligence: the strategic catalyst for a resilient and decarbonised energy future

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Abstract:

Artificial Intelligence in 2026, paving the way to 2030, has evolved from a technological tool to an indispensable strategic catalyst for addressing the challenges of the energy sector. From its initial achievements in optimizing energy efficiency, AI is propelling us toward scenarios of exponential innovation that will enable a sustainable roadmap. AI will contribute to producing, managing, and distributing energy more effectively than other technologies, transforming the energy sector into a decentralized environment. Its potential encompasses robust and scalable solutions where 21st-century Advanced AI—Generative, Foundational Model, and Agentic AI—will create a new paradigm in how energy responds to the challenge of global digitalization. AI in the next five years will not only be regulated but will also adopt industry standards and be surrounded by cybersecurity far superior to anything seen in the past, combining AI with quantum encryption to protect critical infrastructure and sustain mission-critical operations. AI in 2026 is thus presented as a fundamental long-term capability, integrating technology, talent and solid governance to make the most of its potential in a responsible manner.

Keywords:

Decarbonization, Energy Sustainability, Cybersecurity, Energy Efficiency, Critical Governance.

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ENERGY AND STRATEGY

CYBERSECURITY AND SYSTEM RESILIENCE

COUNTERACTING SOCIAL ENGINEERING DRIVEN BY AI

PREVENTION OF 'SIDE MOVEMENT' WITH MICROSEGMENTATION

DEFENCE AGAINST "DATA POISONING"

BENEFITS FOR POWER PLANTS (2025)

FEATURE	IMPACT ON SAFETY	STATE OF THE INDUSTRY IN 2025
FOCUSED ON IDENTITY	PREVENT STOLEN PASSWORDS FROM CAUSING BLACKOUTS	STANDARD FOR ALL NEW EU AND US NETWORK PROJECTS
CONTINUOUS MONITORING	DETECTS 'INSIDER THREATS' OR COMPROMISED AI IN REAL TIME	INTEGRATED WITH DEEPMIND-STYLE ARTIFICIAL INTELLIGENCE MONITORS
ASSUMING A BREACH IN CYBERSECURITY	THE SYSTEM REMAINS FUNCTIONAL EVEN DURING AN ACTIVE ATTACK	REQUIRED BY NERC CIP AND NIS2 REGULATIONS
MINIMUM PRIVILEGE	EMPLOYEES ONLY SEE WHAT THEY NEED TO DO THEIR JOB	REDUCE INTERRUPTIONS RELATED TO HUMAN ERRORS BY APPROXIMATELY 40%

THE ENVIRONMENTAL FOOTPRINT OF AI

ALGORITHMIC 'SLIMMING' TECHNIQUES

HARDWARE: THE TRANSITION TO THE EDGE

CONSCIOUS CARBON FOOTPRINT PROGRAMMING

THE ENERGY TAX OF 'REASONING'

THE DEPLOYMENT OF GREEN AI

SUMMARY

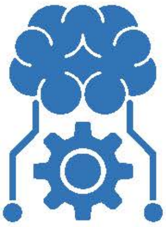
TECHNIQUE	POTENTIAL ENERGY SAVINGS	STATUS (END OF 2025)
MIX OF EXPERTS (MOE)	~90% REDUCTION	STANDARD IN NEW FRONTIER MODELS
QUANTISATION (1 BIT/ 2 BITS)	4X - 8X REDUCTION	RAPIDLY ADOPTED FOR MOBILE AI
AI IN THE DEVICE (EDGE)	100X - 1,000X	INTEGRATED INTO MOST NEW CONSUMER ELECTRONICS PRODUCTS
CARBON-CONSCIOUS PROGRAMMING	~30% CARBON REDUCTION	MANDATORY UNDER MANY CORPORATE ESG POLICIES

IMPACT OF LARGE VS. SMALL MODELS (2025)

METRICS	LARGE GENERAL MODEL (E.G.: GPT-4)	SPECIFIC MODEL FOR SMALL TASKS (E.G.: MISTRAL/SLM)
ENERGY CONSUMPTION	HIGH	90% LOWER
WATER COOLING	~500 ML FOR EVERY 10-50 CONSULTATIONS	SCARCE
INFRASTRUCTURE	MASSIVE HYPERSCALE DATA CENTRES	LOCAL 'EDGE' DEVICES / NPU
LATENCY	SUPERIOR (CLOUD-DEPENDENT)	REAL TIME

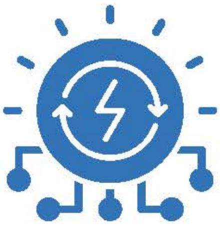
ARTIFICIAL INTELLIGENCE

EVOLVING FROM HIGH-PERFORMANCE COMPUTING TO AI



HPC COMPARED TO AI

HPC	AI
BASED ON SPEED AND FORCE BRUTE CALCULATIONS	FOCUSES ON SIMULATING INTELLIGENCE AND LEARNING PATTERNS
FOCUSED ON SOLVING LARGE AND COMPLEX COMPUTATIONAL PROBLEMS AS QUICKLY AS POSSIBLE	SIMULATES HUMAN INTELLIGENCE, ALLOWING MACHINES TO REASON, LEARN, PERCEIVE AND MAKE DECISIONS
PREDEFINED DETERMINISTIC ALGORITHMS THAT EXECUTE INSTRUCTIONS EXACTLY AS THEY WERE PROGRAMMED	NON-DETERMINISTIC ALGORITHMS THAT LEARN FROM DATA AND MAKE PREDICTIONS OR CLASSIFICATIONS
A PRECISE NUMERICAL RESULT OR A HIGH-RESOLUTION SIMULATION IS OBTAINED	A LEARNED MODEL IS CREATED TO PREDICT A RESULT THAT IS DIFFICULT TO CALCULATE USING OTHER METHODOLOGIES
HPC SIMULATIONS REQUIRE HIGH COMPUTATIONAL COSTS FOR REPEATED EXECUTION FOR UNCERTAINTY ANALYSIS	BETTER ADAPTED TO CURRENT CHALLENGES IN THE FIELD OF UNCERTAIN AND NON-LINEAR SITUATIONS
REQUIRES AN EXPLICIT PHYSICAL EQUATION	LEARN AND ADAPT FROM COMPLEX, CONFUSING AND INCOMPLETE OPERATIONAL DATA



THE ROLE OF AI IN THE ENERGY SECTOR IN THE 21ST CENTURY

FUNDAMENTAL AI METHODOLOGIES	TECHNOLOGIES THAT ENHANCE AND AMPLIFY THE DEPLOYMENT AND USE OF AI
MACHINE LEARNING (ML)	DIGITAL TWINS
DEEP LEARNING (DL)	IoT AND SENSOR NETWORKS
GENERATIVE AI (GenAI)	EDGE COMPUTING
AGENTIC AI	5G AND 6G CONNECTIVITY
WORLD MODELS	BLOCKCHAIN

Executive summary: The AI Imperative

The energy sector is at a pivotal moment, grappling with the complexities of decarbonization, decentralization of power generation, and exponential growth in electricity demand. In this context, artificial intelligence (AI) has evolved from what in past decades was developed through statistical models and scenario planning towards high-performance computing[1] (HPC) and the training of algorithmic machine learning models during the 2000s. But this almost linear trajectory has recently been challenged by advanced AI models that have disrupted technological innovation in the energy sector with models beyond the mathematical algorithms of structured data[2]. This trajectory has made AI a powerful tool with a strong strategic imperative to face the challenges of the energy sector and forge more efficient, sustainable, and resilient solutions.

Key drivers of the AI energy revolution

AI's growing role is directly linked to the fundamental changes that are transforming the energy industry. These drivers are not isolated. Rather, they form a feedback loop that makes AI a necessity that cannot be postponed, as market competition is demonstrating that it is not only a viable solution, but oftentimes the only solution.

Decarbonisation

The global commitment to a low-carbon future has led to a dramatic increase in renewable energy sources, such as solar and wind. These sources are inherently variable and intermittent, introducing unpredictability into the power grid that traditional static management methods cannot deal with. AI is essential in managing this variability by forecasting renewable energy production and balancing supply and demand, facilitating greater penetration of clean energy and carbon footprint reduction.

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[1] HPC stands for high-performance computing.

[2] The distinction between structured and unstructured data is critical to modern data management, storage, and analytics, especially with the rise of advanced AI. The main difference lies in the presence or absence of a predefined data model or schema. Structured data is not just numbers; it usually includes text (and dates, times, currency, etc.) that can be perfectly stored in a traditional database. Unstructured data can contain numbers, but they are often difficult to extract without special and complex AI/ML (NLP/Computer Vision) tools to analyse.

Decentralisation and digitalization

The proliferation of distributed energy resources, such as rooftop solar panels, microgrids, and battery storage systems, is decentralising power generation and creating a complex, multi-directional flow of energy. This change requires an intelligent, highly digitalised grid that can manage vast amounts of data in real time to ensure stability. AI provides the only scalable solution to process this data and automate the complex supply-and-demand management tasks in these modern smart grids.

Electrification

Accelerated electrification of the economy, particularly with the growth of electric vehicles (EVs) and energy-intensive data centres, is putting unprecedented pressure on existing grid infrastructure. This surge in demand requires a new level of intelligence for network optimization and load management. AI is critical to forecasting these new load profiles and adjusting distribution to prevent blackouts and ensure reliability[3].

Understanding AI and its transformative power

Today, AI is already more than a technology. It works as a system of systems that encompasses the different types of advanced AI, such as generative AI4, agentic AI5, deep learning AI,6 and frontier models7 — foundation models, large language models,

[3] Top 10 applications of AI in the energy sector | FDM Group, 26 August, 2025
[4] Generative AI is a type of artificial intelligence that uses deep learning models trained with massive datasets to create content in response to the user's request. Unlike traditional AI, which only classifies or analyses existing data, generative AI learns the underlying patterns and structures of its training data to autonomously produce understandable results such as text, images, audio, video, or software code. This capability lets it empower human creativity and automate complex content generation tasks.
[5] Agentic AI refers to advanced systems that display autonomy and and an ability to act, meaning they can set their own sub-goals, plan a sequence of actions, execute them using various tools, and adapt to changing environmental conditions to achieve an overall goal with minimal human intervention. Unlike generative AI, which creates content reactively (for example, drafting a report on demand), agentic AI is a proactive executor that coordinates multiple steps and systems (for example, drafting a report, archiving it in the database, updating a dashboard, and e-mailing the summary to a team).
[6] Deep learning is a specialised subfield of machine learning that uses complex, multi-layered computer models, called deep neural networks, to analyse data. The term 'deep' refers to the structure of the network, which consists of numerous interconnected hidden layers that process information hierarchically, similar to the human brain. This architecture allows the model to automatically learn increasingly abstract and complex features from raw and unstructured data (such as pixels in an image or words in a sentence) without the need for explicit human programming for feature extraction, allowing it to excel at sophisticated tasks such as language translation, image recognition, and autonomous driving.
[7] 'Frontier models' is a collective term for the most advanced, large-scale, general-purpose AI systems in existence today that push the boundaries of artificial intelligence capabilities. These models are typically foundation models, trained with massive amounts of data and computation, and are characterised by their ability to perform a wide

multimodal models, emerging capabilities, and state of the art[8] — forming an interdependent ecosystem that is joined by the universe of data to be processed, the software and hardware that are used to carry out this task, as well as the processing semiconductors that are required to execute the actions required in energy management and distribution. However, this technological infrastructure could not be executable if it lacked the greatest competitive attribute: human intervention specialised in data analysis, inference, and cognition modelling, and the contribution of professionals in the energy sector who can evaluate the value provided by AI as an operating and execution system. Alongside specialised human capital, business protocols and processes created specifically for AI to execute its potential now emerge with greater relevance.

Thus, the future of the sector in the second quarter of the current century now appears increasingly dependent on the contributions that AI makes and, convinced of its ability to produce, manage and distribute energy in a way that is superior to other technologies, it is committed to radically transform an industry of traditional and static systems into one of dynamic, intelligent, and proactive networks and operations[9], overcoming mindsets and attitudes of the past and charting a new road map of transcendental vision towards a transmuted, enhanced, and superior energy sector.

Given this panorama of opportunities and potential, it should be noted that, since the 1960s, data analysis and high-performance computing have made the energy sector one of the most innovative and transformative industries. AI did not 'arrive' at this sector unexpectedly, as has been the case in other sectors, but was sought in research and development processes as a tool that would allow a technological leap from high-performance computing (HPC) to address the kinds of challenges that have emerged in recent decades and to which HPC does not fit as a viable solution.

Whilst traditional AI has provided enormous advances in automation, detection, prediction, and expanded its reach to unstructured data — the words, images, and videos that must be extracted and reclassified — this AI of operational efficiency is not the advanced, autonomous, and dynamic AI in its cognition that we find impossible to compare with

variety of complex tasks in different domains (such as reasoning, coding, and text, image, and audio generation) with cutting-edge performance. Because of their unprecedented scale, they often exhibit emerging capabilities that were not explicitly programmed and, therefore, imply the potential for social impact, whether positive or dangerous.

[8] 'State of the art', sometimes abbreviated as SOTA, refers to something that is the latest and newest in development.

[9] The Emergence of AI in the Energy Sector - The Energy Consortium, https://theenergyconsortium.ca/assets/pdf/Emergence_of_AI.pdf

traditional AI, as the former's learning and execution have revealed its development of multidimensional thinking. This new and advanced AI not only seeks to reduce costs or improve operational efficiency, but also endeavours to create solutions to challenges that, in the recent past, the energy sector resigned itself to accepting as impossibilities because human beings and the technologies of that time did not cope with their complexities, such as controlling plasma in fusion to generate energy (one of the fundamental challenges faced by fusion energy for more than 70 years and among the keys to making it commercially viable, as mentioned in chapter III of this book[10]). This is a creative AI that seeks to learn on its own, manage itself autonomously, and where the human contribution is fundamental in accepting its results or rejecting them. The domain where humans can still execute advanced AI control lies in the choice of data to be processed, the formulation of hypotheses and strategies on how a model can be trained, and the assurance that the model is safe and trustworthy. That is why, in the last five years, we've begun talking about technically sound and scalable AI, because its developments are being oriented towards huge industrial sectors of vital importance to humanity.

AI in 2026 has two aims to be achieved: the creation of a new value framework in innovation beyond high-performance computing, and the assurance that it is safe, not only from a perspective of ethics and data governance guarantees, but that AI can be considered trustworthy: that is, technically appropriate for its intended use, and standardised and certified for use in industrial sectors and in society. Beyond regulatory requirements, which obey government policies regarding market controls and goals for societal well-being - still falling short in demanding that AI can be certified just like other advanced systems in other high-risk industries such as aerospace, it should be noted that AI is a system in continuous development, versatile and in constant evolution, and therefore it has been very complex and challenging in these years of the birth of advanced AI to create both absolute and immutable regulations and certification standards. However, it is important to observe that, since mid-2024, agencies such as ISO and IEEE have pursued this objective, making great

[10] Since the first attempts to build nuclear-powered machines in the late 1940s, scientists have been stuck in a cycle of creating stellar energy on Earth through nuclear fusion, only to see this possibility vanish in milliseconds because the plasma became unstable. In the 1950s, scientists observed this phenomenon in the first fusion devices that were built, in which the plasma twisted and curled, touching the walls and cooling instantly. Between 1990 and 2010, machines such as JET (UK) and TFT (USA) managed to produce fusion energy but were only able to hold it for seconds. The controls were based on rigid mathematical calculations that could not react quickly enough to the chaotic nature of the plasma. In 2022, DeepMind and the Swiss Plasma Center demonstrated that AI could 'learn' the behaviour of simulated plasma and then control the current flowing through the magnets generated by the magnetic field responsible for plasma confinement and stability, a revolutionary development.

progress in seeking standardisation that can be implemented in the next two years as an acceptable way to mollify some countries' rejection of regulation as the only solution to the detriment of innovation.

Evolving from High-Performance Computing to AI

High-performance computing (HPC) has a long history in the oil and gas industry, though it is far from exclusive to the sector. The transition to a modern, data-intensive power grid has made HPC equally indispensable for utilities, renewable energy developers, and grid operators around the world. HPC is a crucial and growing technology across the energy sector and it has managed to solve enormous challenges. However, advanced AI has now begun development in the sector parallel to other tools, but with superior capabilities and more adaptable to contexts in which HPC has not offered an absolute solution or has made it necessary to continue using past computing paradigms.

HPC in the oil and gas industry (traditional approach)

The oil and gas industry was an early commercial adopter of high-performance computing (HPC) and has pushed the boundaries of supercomputing for decades. Its use is mainly concentrated in the upstream segment (exploration and production).

Application	Purpose
Seismic data processing	HPC processes the huge datasets generated by seismic surveys to create high-resolution 3D and 4D subsurface images. This helps geoscientists accurately identify the location of oil and gas deposits and how they evolve over time.
Reservoir simulation	HPC runs complex mathematical models to simulate the behaviour of fluids (oil, gas, water) within a reservoir. This is essential for optimising drilling locations, predicting production rates, and maximising hydrocarbon recovery.

Application	Purpose
Computational fluid dynamics (CFD)	Modelling of fluid flow in pipelines, refineries, and drilling equipment to ensure safety and improve efficiency.
Materials science	Accelerating the design and testing of new materials (e.g., alloys, polymers) needed for equipment operating in extreme well or deepwater environments.

HPC in the electricity sector (the new frontier)

In the power sector, HPC is essential to managing the complexity of the modern smart grid and integrating variable renewable energy sources.

Application	Purpose
Renewable energy forecasting	High-performance computing (HPC) runs advanced weather and atmospheric models (such as computational fluid dynamics or CFD) to predict production from intermittent sources, such as wind and solar farms. This is crucial to maintaining grid stability.
Grid and power flow analysis	Performs complex and laborious calculations, such as optimal power flow (OPF) and power flow (PF) analysis, in near real-time. This helps operators ensure grid reliability, prevent outages, and minimise power losses, especially on extensive, interconnected grids.
Climate modelling and resilience	HPC simulations model the impact of extreme weather events (e.g., hurricanes, heat waves) on physical grid infrastructure, helping utilities plan for resilience and predict maintenance needs.
Nuclear reactor simulation	HPC is used to model neutron transport, heat transfer, and long-term fuel behaviour in nuclear reactors, for both safety analysis and next-generation reactor design.

Application	Purpose
Discovery of new materials	Accelerate research and development of new and more efficient materials for batteries, solar cells, and high-temperature components in power generation.

High-performance computing (HPC) is based on speed and brute force calculation, focusing on solving large and complex computational problems as quickly as possible (for example, weather modelling or fluid dynamics simulations), whilst AI focuses on simulating intelligence and learning patterns by allowing the machines that simulate human intelligence, to reason, learn, perceive, and make decisions. The differences between one and the other are revealed in the essence of their methodologies: whereas in high-performance computing a massive number of predefined deterministic algorithms are executed by parallel processing, which implies executing the instructions exactly as programmed, with AI non-deterministic algorithms are used (for example, machine learning, or deep learning, to learn from the data and make predictions or classifications). The results achieved with both are unequivocally unique: whilst high-performance computing achieves an accurate numerical result or a high-resolution simulation (for example, a weather forecast or a molecular structure), with AI a learned model is created that can predict a difficult result to calculate through other methodologies: for example, 'The price will go up', or 'The machine is about to fail'.

High-performance computing does not exclude AI, and vice versa. The parallel evolution of both has been taking place since the decades of the '60s and '90s in the 20th century. High-performance computing allowed 2D/3D seismic data and static numerical simulations of reservoirs to be run on centralised computers, assigning limited data interpretation decisions to human experts. With the arrival of advanced AI starting in 2018, these calculations have been carried out using deep learning to achieve a fast and highly accurate interpretation of vast seismic and geological data. By using digital twins, downhole data is integrated in real time with historical models, providing dynamic and adaptive production forecasts and optimizing the location of wells with far greater accuracy. If in the 20th century scheduled maintenance, manual inspections, and simple inventory/demand models were carried out manually, as of 2010 machine learning has created predictive maintenance, analysing data from pump, pipe, and turbine sensors in order to predict failures, thus minimising costly unplanned downtime. AI-based operational efficiency has managed to optimise logistics, manage refinery performance, and forecast demand more accurately, thus improving profitability and reducing waste. Today, artificial vision based on AI monitors installations in real time to detect unsafe behaviours or anomalies in equipment. Risk prediction models analyse historical data, climate and operational records to forecast high-risk conditions, making it easier to monitor emissions and optimise energy consumption to meet sustainability goals.

In recent years, we can see how the use of AI has become more widespread in the energy sector, as its ability to adapt to current challenges is superior to that of traditional high-performance computing (HPC). This is due to the Earth's subsurface being inherently uncertain and non-linear, and traditional simulations therefore requiring a high computational cost for the repeated execution need to analyse said uncertainties. This makes AI the tool which offers the ability to learn and adapt from complex, confusing, and incomplete operational data without needing an explicit physical equation, because the AI learning and prediction environment is based on clarifying uncertainty. AI, by entering industries that collect data from the physical world, is evolving to create what is called a 'world model'.

Evolving towards an AI of world models

Whilst today's large language models (LLMs[11]) possess great abilities to predict the next word in a sentence, they don't really understand why a glass breaks after you drop it or how a car manoeuvres at an intersection in the rain. Traditional AI is reactive: it captures an input and produces an output. A world model, however, has an internal representation of reality that allows it to simulate the future. The most frustrating failures of AI are often due to a lack of basic physics or social intuition. Developing a world model is the main way to endow AI with common sense, and the energy sector has become the largest and most transcendental testing ground that will, quite literally, usher in a radical transformation in how AI evolves and responds to the enormous challenges ahead.

In the energy sector, world models are being developed as high-fidelity digital twins of physical systems, such as the global climate, a power grid, or a fusion plant. By 2026, major

[11] Large language models.

players in this space will focus on the 'AI of physics', where neural networks are constrained by the actual laws of thermodynamics and electromagnetism. The competitive landscape in these types of developments has NVIDIA developing the most advanced literal world model for energy and climate. Earth-2 is its digital twin of the entire planet that uses generative AI[12] to create kilometre-scale weather and climate simulations. Utilities use Earth-2 to predict extreme weather events, such as windstorms or heatwaves, weeks in advance to protect the power grid. Partnering with Siemens, they are building 'industrial AI' models that simulate entire power plants or factories in a virtual world before laying a single brick. DeepMind is applying the principles of world models to solve the most complex physical energy control problems, such as the simulation and control of the plasma inside a tokamak-type fusion machine. This world model of a sun-like environment allows AI to test how to control the current flowing through the superconducting magnets of the fusion device to keep the plasma stable. Another of its developments, WeatherNext 2, is based on weather prediction AI models that already outperform traditional supercomputers. With regard to renewable energies, this is vital to accurately predict the amount of solar and wind energy available at any given time. In 2026, it began a collaboration with the US Department of Energy (DOE), Genesis Mission, (DOE) to use cutting-edge models (such as Gemini) in materials science, discovering new chemical compositions for batteries and carbon capture materials.

Meanwhile in Europe, the development of energy-centred world models differs from the US approach. Whilst the US landscape is heavily driven by private tech giants, the European strategy is a mix of state-backed scientific initiatives and industrial engineering. For 2026, Europe will seek to position itself as a leader in digital twins, essentially high-fidelity global models of physical surroundings and the planet itself. By 2026, the EU is expected to have moved towards a pan-European digital twin of the power grid. This project integrates the local grid models of 27 countries into a single giant world model of the continent's energy flow. This is crucial, as Europe's energy security now depends on sharing wind power from the north and solar power from the south in real time. The EU's flagship world model project, Destination Earth (DestinE), is a large-scale, multi-year initiative by the European Commission, the European Space Agency (ESA), and the Common European Power

[12] CorrDiff is the corrective diffusion model created by NVIDIA to act as a 'smart magnifying glass' on climate world models.

Market Physics Model (CEPMPM)13 to create a digital replica of all Earth systems by simulating the atmosphere, oceans, and land with unprecedented resolution at 1-km scale, allowing European energy providers to simulate how a weather phenomenon of one occurrence in 100 years would affect North Sea offshore wind farms or solar production in Spain, thus providing the most accurate mental map of the world's future energy availability.

A secure and trustworthy AI for the 21st century

AI's versatility in solving challenges with creativity and scalability is surprising both regulators and industry standards agencies, as AI is being developed and deployed in contexts never before conceived and at remarkable scale. Stagnant situations in the past, devoid of tangible and comprehensive solutions, have been solved thanks to AI's enormous potential.

Developing prediction models with renewed creativity

The development of AI-based solutions is a highly creative process, as possible solutions are explored using a highly versatile technology. One prime example of its elevated creative capacities was solving the deployment of connectivity in emerging markets such as sub-Saharan Africa. This is an enormous challenge for governments in developing countries that also have to face geographies of intense complexity. AI in this context was revolutionary as a solution to obtaining a clear vision of the location of existing power lines and facilitating better decisions on where to concentrate efforts, how to design the grid, and how to obtain the necessary equipment. Until now, space agencies have provided 'eyes in the sky' to developing countries, extending the capabilities of geostatic satellites to visualise geographies with accuracy down to the centimetre. However, AI is moving with great power to supplement and optimise where satellites do not reach. To demonstrate how AI can map medium voltage (MT) infrastructure in African countries with high precision, the AI division of U.S. company Meta formed a research consortium with the World Bank's Energy Sector Management Assistance Program (ESMAP); Sweden's Royal Institute of Technology (KTH), one of Europe's leading universities in engineering; the World Resources Institute

[13] Common European Power Market Physics Model

(WRI), an institute of the MacArthur Foundation in Washington, D.C. whose non-profit mission is to improve people's lives, protect and restore nature, and stabilise the climate; and the University of Massachusetts at Amherst. Together, they developed a new predictive model to map medium-voltage (MV) infrastructure using public data and assumed data. To develop the model, the first step was to locate electrification at the settlement level by detecting nighttime radiance through the VIIRS day-night band sensor on NASA satellites that provided infrared radiometry images. The next step was to follow the power grid through its connecting power lines. The grid estimation algorithm sought to establish connections as efficiently as possible, using known power grids as templates, but also basing its recommendations and predictions on choosing grid routes that follow roads, avoid water, and prefer shorter routes. This second set of data was what helped the model to not only correctly predict power line routes but also to improve the results obtained only with Real World Data (RWD), such as power lines that could be seen at night without the need for satellite vision. This pilot experiment successfully achieved its purpose and has become a model that can allow governments and NGOs to use it with certainty to understand where people need electricity or where to expand water pumping infrastructure to provide basic services. The results of this model were made publicly available through the World Bank's open energy data repository, which ensured that the data could be used by governments, nonprofits, and other organisations focused on improving energy access. The great power of advanced AI is its enormous scalability for use in a wide variety of scenarios, solving diverse purposes and needs with ease and creativity without barriers.

A new concept of infallibility in prediction

AI does not need to predict with 100% infallibility to be trustworthy. In fact, when AI models in training reach an assumed 99% infallibility, it is suspected that learning has deteriorated, often indicating 'overfitting' or that the model has memorised historical training data but performs poorly when exposed to new real world data (test accuracy or out-of-sample performance). In the energy sector, real world data plays a very important role in the reliability of the model, and that is why one of the recent arguments for the reliability of advanced AI in creating guarantees that the model can be certified or standardised will come from companies in the energy sector that begin to develop data governance strategies that include how to treat real world data (RWD).

The security of AI systems in an increasingly vulnerable world

Whilst the opportunities are immense, so are the challenges. The digitalisation enabled by AI also generates new vulnerabilities, making cybersecurity a primary concern. As utilities integrate AI to manage everything from smart grids to fusion plants, they simultaneously open up a new digital frontier that both state actors and cybercriminals are rushing to exploit. The energy sector is no longer just defending against human hackers: it is also defending against adversarial AI. In 2025, the average time it takes for an AI-assisted security breach to penetrate a network dropped to just 11 minutes14, compared to the days or weeks of traditional attacks. Malicious AI can map the entire topology of a power grid in seconds, identifying 'weakest link' sensors or legacy hardware that human analysts might miss. To counter this, energy companies have implemented a strategy called 'AI Guardians': autonomous security systems that battle in real time with attacking code and make tactical defence decisions at machine speed without waiting for human approval. As we move toward a decentralised energy future (with millions of solar panels, electric vehicle chargers, and home batteries), the 'attack surface' has grown exponentially. Therefore, the energy sector is beginning to combine AI with strong quantum encryption. As AI can decode current encryption methods much faster, the next step in protecting our key infrastructures such as AI-powered fission reactors and fusion plants 15 is to move towards a zero-trust architecture, where each data packet is verified by a separate AI security layer before it can circulate over the network.

It is absolutely essential that, in parallel to the development and deployment of AI in any sector, solid barriers and cybersecurity strategies are built around it that guarantee the protection of infrastructures and the sustainment of operations.

[14] The Network Installers, 'AI Cyber Threat Statistics: The 2025 Landscape of AI-Powered Cyberattacks,' 2 December 2025

[15] Understanding the difference between fission and fusion is key to understanding the future of energy. In simple terms, they are opposite processes: one breaks atoms and the other combines them. The former is a constant, powerful energy source that does not emit CO2, but produces radioactive waste that lasts thousands of years, and there is a risk (albeit low) of an accident if the chain reaction is not properly controlled. Nuclear fusion, on the other hand, releases much more energy than fission, about four times more per kilogram of a fuel (which is almost inexhaustible because it is taken from sea water), does not produce long-lasting radioactive waste and is intrinsically safe (if something fails, the reaction stops on its own). Its challenge is that it is extremely difficult to achieve on Earth. Projects such as ITER that recreate the conditions of the sun's core through giant magnets and ultra-powerful lasers, are opening a gap in fusion where AI is an essential element to make it commercially viable.

Towards sustainable, energy-efficient AI

The significant energy and water consumption of AI data centres present a profound paradox: the same technology designed to drive energy efficiency also imposes significant new pressure on the power grid. In addition, addressing ethical considerations, data privacy, and the global talent gap requires a well-structured and well-defined governance framework. The strategic imperative for energy sector leaders is to move from a fragmented, project-based approach to a holistic strategy that views AI as a critical long-term capability, integrating technology, talent, and strong governance to responsibly realise its full potential.

Despite the challenges, it is undeniable that AI will turn the energy sector into one of the most proactive industries in charting humanity's future well-being, its energy prosperity, and carving out a future that, at the same time, demonstrates that energy resources can be managed sustainably, and that the digital civilisation that governments and the public sector are building will be supported by a strategic, valuable, and responsible sector to create the economic and social progress of the 21st century.

The strategic context: market drivers and maturation

The adoption of AI in the energy sector is not an incipient trend but a fundamental maturation of the market driven by the convergence of powerful forces at the macro level that reinforce themselves. The industry is moving beyond a 'pilot or planning' phase geared towards implementing practical, scalable solutions and building internal capabilities. This transition is a direct response to the increasing complexity and interconnectedness of the modern energy landscape.

The use of artificial intelligence (AI) in the energy sector has evolved significantly from early rule-based systems to today's complex machine learning models. The emergence of AI in the energy sector is a transformative evolution. Initially, the industry relied on static, manual, and often reactive processes, where data was stored in silos and decisions were based on historical norms and rigid deadlines. The advent of AI introduced a new paradigm focused on real-time data analysis, predictive capabilities, and intelligent automation in response to the growing complexity of the power grid, the need to integrate variable renewable energy sources, and the pursuit of greater operational efficiency and safety. In the oil and gas sector, the need to more accurately identify potential reserves and optimise drilling routes to reduce costs and risk (e.g., 'dry wells') has allowed AI and its immense capabilities to analyse large amounts of seismic and geological data to solve this challenge. Likewise, and perhaps most relevant is the use of AI-powered digital twins (virtual replicas of assets such as power grids, pipelines, platforms or refineries) that are used for real-time operational monitoring, simulation, and optimisation. These advances in energy efficiency have similarly brought advances in materials science, as AI is accelerating the discovery and co-design of new battery materials and solar technologies that pivot from traditional 20th century paradigms.

The road map for innovation towards challenge-responsive AI can be mapped out over decades:

The early years (1970s–1990s): Expert systems

In the initial phase, AI applications were mainly based on rule-based systems or expert systems. These systems sought to encode the knowledge and decision-making processes of human operators into computer programs. Their primary applications focused on detecting and diagnosing faults in power systems, identifying anomalies, and diagnosing equipment faults based on a predefined set of rules. In the oil and gas sector, early models were used to simplify decision-making in exploration and reservoir management.

The rise of machine learning (1990s–early 2010s): Neural networks and prediction

In the mid 1990s, the use of fundamental machine learning techniques, such as artificial neural networks and support vector machines, began to increase thanks to increasing computational capacity. Historical data could be used for more accurate prediction and neural network-based forecasting to predict load and price more accurately based on electricity demand, supply, and price data, which is crucial for market operations and grid scheduling. In the oil and gas sector, machine learning models began analysing equipment sensor data to predict failures before they occurred, moving from time-based maintenance to a proactive AI-driven predictive maintenance strategy which, instead of adhering to calendar-based static schedules or waiting for equipment to fail, uses machine learning to analyse sensor data and historical performance metrics and predict when equipment is likely to fail. The benefits are substantial, including reduced unplanned downtime, longer equipment life, and lower maintenance costs.

Machine learning has also made it possible to forecast renewable energy. The intermittent nature of solar and wind presents a significant challenge to grid stability. AI provides a solution by processing vast amounts of real-time data from weather stations, satellite imagery, and historical performance metrics to produce highly accurate predictions of power generation. This improved accuracy allows grid operators to optimise energy distribution and storage, making renewable energy more reliable and accelerating its integration into the grid.

The era of smart grids and big data (2010s–present): Deep learning and optimisation

The confluence of the concept of smart grids, the proliferation of sensors (IoT), and the massive increase in data coming from smart meters and renewable sources has led to the widespread adoption of advanced AI. This made it possible to solve the management of the bidirectional flow of energy and the variability that sources such as wind and solar drove an important innovation in AI towards the management of smart grids. Likewise, deep learning models (a subfield of machine learning) significantly improved the accuracy of wind and solar production forecasts up to 36 hours in advance, which allowed for greater grid stability and greater penetration of renewables thanks to their optimal integration into the grid. AI algorithms, by managing complex grid operations in real time, including balancing supply and demand, and optimising voltage and power flow to reduce power losses, have enabled an exponential operational efficiency increase in smart grids, a point of no return that forces the sector to continue plotting this roadmap towards automated operability.

Current trends (focus on generative AI and resilience)

By exploring advanced AI, particularly large language models (LLMs), the energy sector has begun to process, summarise, and automatically ensure regulatory compliance in complex technical and regulatory documents. More relevant still is the work being done in areas of cybersecurity and resilience, where AI-based tools are essential to monitor critical infrastructures and predict and mitigate network disruptions caused by cyberattacks or extreme weather events.

This technological shift is a strategic imperative to addressing some of the most pressing global challenges, such as climate change, energy security, and the growing demand for clean and reliable energy, marking a significant step toward a more innovative and sustainable energy future.

The AI toolkit

The application of AI in the energy sector is underpinned by a diverse and increasingly sophisticated set of technologies and methodologies. The field is evolving beyond generic algorithms to specialised, integrated systems that leverage domain-specific knowledge to solve crucial problems.

Fundamental AI methodologies

Machine learning (ML)

ML is AI's foundational technology, which uses algorithms that learn from data to make predictions or decisions. This includes supervised learning for tasks such as forecasting energy consumption based on historical data as well as unsupervised learning to identify patterns in unlabeled data, such as market behaviour or consumer segmentation.

Deep learning (DL)

A subset of ML, deep learning models are used for more complex tasks that require processing large sets of data. Examples include image recognition to analyse drone images of power lines for defects and nonintrusive load monitoring (NILM)[16] to disaggregate device-level energy consumption only using smart meter data[17].

Generative AI (GenAI)

GenAI is a powerful class of models capable of creating new and original content. In the energy sector, its applications extend beyond simple text generation to include summarising extensive technical reports, enabling rapid knowledge transfer for new engineers, generating code from natural language instructions, and creating synthetic images to simulate new transmission line routes or train defect detection models[18].

Technologies that facilitate and amplify AI's deployment and use

AI's effectiveness is amplified by its integration with other parallel advanced technologies:

Digital twins

A digital twin is a virtual representation of a physical asset, system, or process that is continuously updated with real-time sensor data. These dynamic models allow scenario simulation, predictive analysis and testing of operational changes without affecting the physical system. For example, digital twins are used to predict corrosion in steam generators, saving utilities billions in costs annually. Even as digital twins create digital representations of the real world, a powerful trend is the development of physics-based neural networks[19,] which integrate physical laws and equations into the AI learning process,

[16] Nonintrusive Load Monitoring (NILM), also known as energy disaggregation, is an advanced signal processing and machine learning technique that identifies individual appliances and their energy consumption simply by monitoring the total electricity consumption at a single point, usually the main electricity meter. In essence, NILM solves a complex inverse problem: it takes the total power signal and breaks it down into its components without the need for independent sensors in each appliance.
[17] AI-Powered Demand Side Management: Reshaping when and how we use electricity, 2005
[18] Generative AI in Transmission and Substations - EPRI, AI White Paper 2025
[19] The neural network is forced to learn a function that not only fits the data but also satisfies the fundamental physical law in all the points tested within the computational domain, i.e., that it cannot 'invent' or 'assume' reality but must accept it as the physical data of the real world tells it to be. This is a radical change in the training of these networks which learn by themselves. The impact that real world data (RWD) will impose on AI will accelerate the development of AGI or artificial general intelligence, the super AI that thinks and is aware of what life really is and its analogue realities.

ensuring that predictive models are not only accurate but also physically plausible, which is a fundamental requirement for complex energy infrastructures.

IoT and sensor networks

The proliferation of internet of things devices and sensor networks is the foundational layer for AI applications. These sensors continuously collect real-time data on everything from vibration and temperature to electrical current and voltage. This data provides the necessary fuel for AI algorithms, enabling real-time asset health monitoring, anomaly detection, and data-driven maintenance scheduling.

Edge computing

Whilst IoT collects data, edge computing processes it at the source (e.g., at a wind turbine or local substation) rather than sending it to a central cloud. This achieves a reduction in latency, which is essential for self-repairing networks that must respond to a failure in milliseconds. Greater bandwidth efficiency is also achieved as AI models can filter noise[20] locally, sending only significant anomalies to the central system. Privacy and security are ensured as sensitive energy consumption data can be processed on-site, reducing the risk of data interception during transit.

5G and 6G connectivity

The transition to 5G (and future 6G networks) provides the high-speed, high-density communication infrastructure needed for 'massive IoT'. Segmenting the network allows utilities to reserve an exclusive network for critical AI control signals, thus ensuring that they are not slowed down by public internet traffic. In this sense, ultra reliable low latency communication (URLLC) benefits from AI for the synchronisation of distributed energy resources (such as thousands of household batteries) to thus balancing the network in real time.

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[20] The process of removing irrelevant information from a data set so you can see the 'story' the data is really trying to tell. In data analysis, noise is not sound but any random variation that does not represent the actual trend.

Blockchain

Blockchain acts as the 'layer of trust' for AI, especially in decentralised energy markets. In peer-to-peer (P2P) trading, AI can manage the purchase and sale of surplus solar energy between neighbours, whilst blockchain provides a secure and immutable record for such transactions, ensuring that the data used to train models has not been manipulated by malicious actors or cyberattacks.

Transformative applications across the energy value chain

The impact of AI is not limited to isolated improvements. Rather, it is creating a comprehensive ecosystem of solutions that is redefining key business processes. By moving from reactive to proactive and from manual to automated, the energy value chain is becoming a continuous, AI-optimised cycle that offers tangible solutions on several fronts:

Transmission, distribution, and grid management

Smart grids

AI is central to the development of smart grids that use digital communications technology to detect and react to local changes in usage. AI algorithms analyse real-time data from smart meters and IoT devices to predict consumption patterns, dynamically balancing supply and demand to minimise energy waste and ensure consistent service delivery. This dynamic balance is essential to maintaining grid stability and preventing outages.

Measuring the exact percentage of 'smart grids' in the world is complex, as there is no single global definition of what makes a grid 'smart'. However, energy experts typically measure progress using three main indicators: smart grid completion, smart meter penetration, and digital maturity scores. As of 2026, the global picture breaks down as follows:

Global coverage and finalisation: According to recent industry studies (e.g., Juniper Research, 2025/2026), the world is still in the initial and intermediate stages of transition. It is estimated that smart grids would make up approximately 24.2% of the global grid as of

2025, projecting this to reach of 42.7% by 2030 as the oldest infrastructure reaches the end of its useful life and is replaced by digital systems. There is, however, the '40/40' problem: in regions like Europe, about 40% of the power grid is over 40 years old, which means that a significant portion of the global grid is still powered by analogue technology designed for one-way power flow.

Smart meters penetration (The 'eyes' of the grid): Smart meters are the most visible component of a smart grid. They provide the two-way communication necessary for AI's operation. Total units in global installations exceeded 1.8 billion units by the end of 2024 and are projected to exceed three billion by 2030[21]. The world's smart grid leaders are mainly in North America, with an approximate penetration of 81%, although China has reached a penetration close to 100% in urban areas, acting as a massive data engine for AI-driven network management. Europe, in the meantime, is catching up rapidly (averaging about 72%), driven by EU mandates for decarbonisation.

Fault detection and self-repairing networks

Traditional methods of fault detection are often slow, mostly analogue,[22] and lack predictive capabilities. AI-powered systems are revolutionising this by processing real-time data from sensors to detect anomalies and anticipate faults before they cause serious breakdowns. This is enabling the development of 'self-repairing' networks, which use AI-powered detection and intelligent control systems to autonomously detect, analyse, and respond to failures. These systems can automatically isolate faults and reconfigure power distribution, preventing nearly 45% of potential service outages and minimising power restoration times by up to 60%. This significantly improves grid resilience and reliability.

[21] Counterpoint, 'Global Smart Meter Installations Set to Surpass 3 Billion by 2030 amid Accelerating Adoption,' 11 November 2025

[22] Historically, inspections of high-voltage networks have been carried out almost entirely by humans and helicopters. Recently, drones equipped with thermal vision are rapidly becoming the main tool for this work, but AI is the third-generation tool that is propelling autonomous inspections thanks to autonomous drones that are installed in substations. They take off automatically, fly a programmed circuit of kilometres and return to their base to recharge without any human touching a controller. Instead of one person looking at 10,000 photographs of power poles, artificial intelligence software 'filters' the data and automatically flags only images that show rust or damage.

Outage management

AI improves outage management by using data from smart meters and sensors to determine the exact location of a fault. It can also predict restoration times based on the type of outage, location, weather conditions, and available resources, allowing utilities to provide more accurate and timely information to customers.

Energy markets and trade

Accurate forecasting is crucial to ensure grid stability and security of supply. AI models can be trained with historical data and incorporate a number of additional data sources, such as real-time weather reports and economic indicators, to predict future consumption patterns more accurately. This capacity is especially important for managing the variability introduced by renewable energy sources.

Likewise, the volatility of modern energy markets, driven by the growing share of renewables, is a key motivator for the adoption of algorithmic trading. AI-powered platforms analyse large datasets in real time, providing predictive insights and risk assessments that enable more informed, cost-effective business decisions. These algorithms can execute trades autonomously with limited human intervention, allowing for greater flexibility and faster reactions in dynamic markets. However, this is not a complete replacement for human traders: many companies find that the most valuable approach is a symbiotic relationship where algorithms handle complex computations and data processing whilst human experts make the final strategic decisions based on the results.

Demand management and customer engagement

The energy sector, when it serves the consumer, is making great changes in terms of the services provided, its innovation, and the approach to creating individualised experiences.

Automated charging and control of smart appliances: AI is a key enabler for demand management, which aims to redefine when and how electricity is used. AI autonomously adjusts smart devices, such as thermostats, heat, ventilation, and air conditioning systems, as well as electric vehicle chargers, to shift energy use to off-peak hours. This is made possible by reinforcement learning, which allows AI to understand user preferences and balance energy cost savings with convenience. This capability turns passive consumers into active participants in grid stability.

Personalised information and engagement: AI provides a significant advancement in customer engagement by delivering personalised energy insights. Through technologies such as nonintrusive load monitoring, which disaggregates energy usage from smart meter data, AI can provide customers with detailed, device-specific consumption patterns and efficiency recommendations. This hyper-personalised approach not only promotes energy efficiency but also builds trust and encourages customers to become partners in grid stability.

Customer service and call centre support: Generative AI is revolutionising customer care by powering intelligent self-service tools and AI-assisted agents. By automating routine queries and providing call centre representatives with nuanced, real-time data, AI has been shown to reduce high billing calls and increase customer satisfaction rates.

Navigating the AI energy paradox: challenges, risks, and critical governance

The transformative potential of AI is a double-edged sword. Whilst it allows for unprecedented efficiency, it also introduces new and complex risks and comes with a significant environmental impact. The 'AI energy paradox' is a core challenge that requires deliberate and strategic management.

The operational and technical landscape

The implementation of AI in the energy sector is not without its obstacles. One of the main challenges lies in integrating advanced AI with a legacy infrastructure that was not designed for digitalisation and real-time data flows. This is compounded by the need for high-quality, standardised data, as raw data from smart grids is often incoherent, incomplete, and inconsistent. In addition, there is a recognised talent gap in the industry, with a significant shortage of professionals with technical expertise specialising in both AI and energy-specific operational technology. This lack of expertise in both domains is a critical hurdle to scalable AI adoption.

Cybersecurity and system resilience

The increased digitalisation and connectivity required for AI-based power grids create a rapidly expanding threat landscape. AI-based tools act as a 'force multiplier' in both directions, improving threat detection and enabling more responsive protection whilst empowering adversaries with sophisticated new attack vectors. Specific threats include false data injection and time-delay attacks, where manipulated sensor data can trick control actions and potentially cause network instability. The rise of adversarial machine learning also allows malicious actors to evade detection. Defending against these threats requires proactive, layered defence as well as a new type of workforce that understands both AI/IT and energy-specific OT.

In 2025, cybersecurity reached a new milestone in innovation with zero trust architecture, which has gone from being a theoretical concept to a regulatory requirement for critical infrastructures, particularly in the energy sector. Unlike traditional perimeter security, which acts as a wall around a castle, zero trust treats every user, device, and software component as a potential threat, even those already inside the system, and acts as a specialised defence against these 'next-generation' threats:

A. Countering AI-driven social engineering

Attackers now use generative AI to create hyper-realistic deepfakes of energy executives or 'perfect' phishing e-mails. In these situations, the zero trust defence is oblivious to the human factor. Even if an employee is tricked into revealing their password, the system still requires multi-factor authentication and contextual verification for each action. In addition, the status check of the device is carried out. If the login comes from a device that hasn't been scanned for malware in the past hour, access is instantly denied, stopping the AI-driven breach from the get-go.

B. Prevention of 'lateral movement' with micro-segmentation

AI-powered malware is designed to spread like a virus through the network until it finds the 'brain' (the control center). The zero trust defence divides the network into thousands of isolated 'micro-segments', producing the screen effect: if a hacker infects a smart meter in a residential neighbourhood of a city, it is trapped in that tiny segment. The hacker cannot access high-voltage transmission lines or nuclear cooling systems because there is no route without explicit re-verification.

C. Defence against 'data poisoning'

Malicious AI can attempt to 'poison' the data being sent to the AI of a power grid, for example, by simulating a massive increase in energy demand to cause the system to shut down. With zero trust defence, each AI sensor and 'agent' is assigned a unique digital identity. When analysing the continuous behaviour of each sensor, if one starts sending data that seems 'synthetic' or out of the ordinary, the zero-trust policy engine marks it as 'unreliable'. The system then switches to a backup data source or safe mode until a person can verify the integrity of the data.

Feature	Impact on security	Status in the industry by 2025
Focus on identity	Does not let stolen passwords be the cause of blackouts.	Standard for all new EU and US grid projects.
Continuous monitoring	Detection of 'insider threats' or compromised AI in real-time.	Integrated with DeepMind-style AI monitors.
Assume a cybersecurity breach	The system remains functional even during an active attack.	Required by NERC CIP and NIS2 regulations.
Minimum privilege	Employees only see what they need to do their jobs.	Disruptions related to human error are reduced by approximately 40%.

Summary of benefits for power plants (2025 data)

In the field of nuclear fission, zero trust is already integrated into the design of the small modular reactors currently under development. Although they work with nuclear power, their real value lies in how they can assist with industrial decarbonisation in power grids:

unlike large plants that are difficult to 'turn off and back on', modular reactors can adjust their power quickly to cover the gaps when there is no sun or wind. Since these reactors are typically designed for remote or autonomous operation, they use zero trust to ensure that remote signals are encrypted, verified, and restricted to specific one-way data diodes, making it physically impossible for a hacker to send a shutdown order from outside an authorised control room.

AI's environmental footprint

The 'AI energy paradox' is a key challenge of our time. Whilst AI helps companies reduce energy consumption by up to 60% in some cases by optimising building management and smart grids, the technology itself consumes enormous amounts of energy when it comes to training AI models with trillions of parameters, as is the case in high-computing centres or data centeres of companies dedicated to training large language models (LLMs). 23Until 2022, data centres accounted for about 2% of energy-related carbon emissions, and this included data centres where AI was not trained

Since 2025, the landscape has changed dramatically for those AI companies that have burst onto a market hitherto dominated by large foundational models, mainly developed by US companies. By the end of 2025, there is already much talk about this being the year in which 'Green AI' went from being a niche academic interest to a crucial business requirement, therefore making it impossible to continue with the computational expenditure of previous years, which forecast scenarios that, in terms of energy, are impossible to assume in most countries.

At present, the industry is moving away from the 'bigger is better' philosophy and toward a design that prioritises efficiency. The latest advances and trends in reducing the computational and environmental footprint of AI by the end of 2025 have reconfigured the forecasts of many agencies. Most of all, there has been a paradigm shift in the development of foundational models on which advanced AI is based.

[23] International Energy Agency, 'Electricity 2024. Analysis and forecast to 2026'.

(A) Algorithmic 'slimming' techniques

Researchers have found that much of the energy used by large language models is wasted computing. New techniques are eliminating this waste thanks to the appearance on the market of Chinese models and their new proposals on architecture and model learning. The most revolutionary techniques in 2025 were:

DeepSeek and MoE (Mix of Experts): The Chinese language model DeepSeek, launched in mid-January 2025, presented a unique architecture that allowed it to reduce its needs for high computing, the result of the embargo on state-of-the-art chips and lithographic design tools that the US and Europe imposed on China since 2019. Instead of using all the parameters for each calculation, the model dynamically selects some 'expert' subnets to process the data input. This makes the model faster and cheaper to run, as it avoids the massive memory and power consumption of a fully dense model. This new architecture, inspired by machine learning inference principles, has enabled models to maintain exceptional performance whilst consuming up to 90% less energy per query.

Extreme quantisation (1-bit and 2-bit): Traditionally, AI uses 16 or 32-bit numbers. By 2025, advancements in '1-bit' architectures have allowed models to run with much lower accuracy. This reduces memory use and power consumption by four to eight times, with negligible loss of accuracy.

Knowledge distillation: Large 'teacher' models are used to train 'student' models, which are 10 times smaller but retain more than 90% of their capacity. This makes them efficient enough to run on local devices rather than in massive data centres.

(B) Hardware: the transition to edge computing

Sustainability is driving a massive transition to on-device AI, which avoids the energy-intensive transfer of data to the cloud. The laptops and phones of 2025 now feature dedicated AI chips or NPUs (neural processing units), optimised for 'inference' (execute the AI) rather than 'training'. These chips are 100 to 1,000 times more energy efficient than general-purpose GPUs. The new chips inspired by the human brain (neuromorphic computing) only consume energy when they receive a peak of data. This 'event-based' processing uses a fraction of the electricity of traditional chips running on a continuous clock.

(C) Carbon-aware programming

Google and other cloud providers have deployed 'carbon-smart' platforms through techniques such as time shifting (AI training tasks that are not time sensitive are automatically scheduled for when the local power grid has a surplus of wind or solar power, and localization) or digitally 'teleporting' work loads to data centres in sunny or windy regions, maximising real-time carbon-free energy use.

(D) The energy tax of 'reasoning'

A crucial discovery for 2025 is the 'reasoning gap'. The most recent data as of December 2025 confirms that the new 'reasoning' models (which think step-by-step) can consume between 30 and 700 times more energy than the standard models, as they generate thousands of internal 'thoughts' before giving an answer. To address this, 2025 systems use 'router AI', a tiny, low-power AI that decides whether the user's question is simple (e.g., 'What's the weather like?') or complex. Simple questions are sent to tiny models, thus saving high power for really complex problems.

Technique	Energy saving potential	Status (end of 2025)
Mix of Experts (MoE)	~90% reduction	Standard on the new frontier models.
Quantisation (1-bit/2-bit)	4x–8x reduction	Being rapidly adopted for mobile AI.
On-device AI (edge).	100x–1,000x	Integrated into most new consumer electronics.
Carbon-aware programming	~30% Carbon reduction	Mandatory under many corporate ESG policies.

Chart summarising energy-saving techniques

(E) Deployment of the first 'green AI' commercial developments

Europe is currently a world leader in sustainable AI regulation (EU AI Act) and efficiency research. The most recent specific examples and data for 2025 that deserve to be cited as examples:

1. Spain: The 'prosumer' revolution and smart grids

Spain is leveraging its huge solar and wind capacity by using AI to manage decentralisation, which is inherently more sustainable than centralised fossil fuel plants.

Altano Energy (Madrid): This startup uses AI to manage an integrated clean energy platform throughout the Iberian market. Their AI models analyse consumption patterns to automatically switch customers to the cheapest, greenest electricity available in real time, reducing the need for high-carbon plants for peak hours.

The A3E-INDAL project: This groundbreaking collaboration between the University of Castilla–La Mancha and the technology centre Ainia succeeded in developing AI software that 'mimics an energy expert'. It is specifically designed to run on energy-efficient hardware in food processing factories (such as canned meat plants) to identify energy savings of up to 17% without the need for connection to a massive, energy-intensive data centre.

Endesa and Red Eléctrica: Recent data for 2025 shows that 56% of Spain's electricity currently comes from renewable energy. Spanish utilities use machine learning models (such as Random Forest and XGBoost) to predict energy prices and demand. These models are thousands of times smaller than large language models, but have improved grid stability and significantly reduced waste.

2. Mistral AI (France): The leader who prioritises efficiency

Mistral AI has become Europe's answer to Silicon Valley, but with a radical focus on 'small language models' (SLMs). According to its July 2025 transparency report, Mistral was the first company to publish an 'environmental footprint' report for its Mistral Large 2 model. The prime consequence of this action was to demonstrate that a model 10 times smaller generates impacts with a smaller order of magnitude for the same task. Mistral's strategy encourages companies to bundle AI requests and use the smallest possible model for the task (e.g., using Mistral 7B for a summary instead of GPT-4).

To understand this impact in all its dimensions, just compare Open AI Chat GPT4 and small foundational models24 developed by Mistral and other companies:

Metric	Large general model (e.g. GPT-4)	Specific model for small tasks (e.g., Mistral/SLM)
Energy Consumption	High (comparable to a small town)	90% lower
Water consumption for cooling	~500 ml for every 10–50 queries	Negligible
Infrastructure	Hyperscaled massive data centres	Local 'edge' / NPU devices
Latency	Superior (cloud-dependent)	Real time

Impact of the large vs. small model (2025)

Ethical Considerations and Algorithmic Bias

The deployment of AI in areas of great importance, such as energy infrastructure, raises complex ethical considerations. A key risk is algorithmic bias, as AI models trained with biased data can perpetuate such biases, resulting in unequal access to clean energy or disproportionate exposure to pollution in certain communities. This risk underscores the crucial need for transparency and accountability, ensuring that decisions made by AI systems are explainable and that a human being is responsible for them, especially in an environment in which failures can have catastrophic consequences. In addition, the collection and analysis of large amounts of data on energy consumption raises significant data privacy concerns that must be addressed through robust governance frameworks.

When regulators look at biases in AI and seek to create 'safe' AI, their definition is multifaceted and goes far beyond just preventing physical harm. It encompasses a wide range of principles designed to ensure that AI systems are developed and used in ways

[24] Whilst the term 'foundation model' was coined by Stanford in 2021 to describe models trained with broad data that can adapt to many tasks, the 'small' variant is a specific technical evolution from 2024–2025. A small foundation model (SFM) is a versatile AI model trained with diverse, high-quality data sets that, unlike its 'large' counterparts (LLM), is intentionally designed with significantly fewer parameters (typically less than 10 billion). The goal of an SFM is to achieve performance tailored to 10 to 100 times its size in specific reasoning or specialised tasks whilst maintaining a minimal computational footprint.

that protect citizens, uphold democratic values, and promote trust, seeking equity and inclusion. Therefore, the challenge at the moment is to create 'demonstrable' AI, i.e., one whose decision-making process must be, to a certain degree, understandable. This principle, often referred to as 'explainability,' requires that users and regulatory bodies be able to understand how a high-risk AI system came to a certain conclusion. The goal is to build trust and enable accountability and recourse in the event of a failure.

Geopolitical and regulatory frameworks: shaping the future of AI in energy

The strategic importance of AI transcends the corporate and operational spheres, reaching a geopolitical and national security dimension. The race for AI supremacy is not merely technological. It is closely tied to a nation's ability to provide the 'raw energy' and 'computer security' critical to the operation of such systems. The role of the energy sector is therefore a priority, as a nation's ability to generate and supply reliable and affordable energy is now a critical component of its technological leadership in the age of AI.

The evolving regulatory landscape

Governments around the world are beginning to define the future of AI through proactive regulation. The European Union's AI Act is the world's first comprehensive law on AI, and establishes a risk-based classification system. The energy sector's status as critical infrastructure places it in the 'high risk' category, subjecting its AI systems to strict regulations, including lifecycle assessments and mandatory registration in an EU database. This framework demands transparency and accountability, and defines how AI models are developed and managed.

Where the regulator's reach ends — and perhaps this is the greatest challenge — is in dealing with agentic AI, which makes decisions without consulting the human, for example, when there is a need to act quickly at critical moments and other examples described in previous chapters. The regulatory vacuum regarding how to hold an autonomous system accountable for actions is complicated beyond generative AI and foundation models because it is a completely different operating system that does not include the human in its decision-making processes and which can use other technologies to perform its tasks. In this case, seeking responsibility already expands to third parties and this is a huge regulatory risk. In 2026 and 2027, when thousands of intelligent agents will be operational (perhaps in combination with quantum computing) existing regulations will be forced to modify some of the parameters used in creating principles of accountability and transparency of language models, because agentic AI is not a model but rather an architectural pattern or a system design, instead of a unique 'model' like GPT-4 or Claude.

The specific regulatory 'gaps' that have recently been identified and that will constitute the new framework for efficient regulation can be divided into several fields:

- The 'human-in-the-loop' fallacy: Many regulations assume that a human will review the AI result before using it. In agentic AI, the goal is to eliminate the human from the cycle to gain speed and scale. Current laws do not yet have clear rules for 'human-in-the-loop' (where only humans oversee) or 'human-out-of-the-loop' systems.
- 'Chain' liability: If an agent is created that uses an OpenAI model, a Google search tool, and a Stripe payment tool, and that agent makes an illegal purchase, the regulatory framework has to calibrate where the liability resides and how. The current focus of EU AI Act on the 'supplier' of the base model does not fully cover the 'orchestrator' who connected all those tools.
- Sandboxing and 'blast radius': The risks of generative AI mainly concern information. Agentic AI risks are operational. Existing laws focus on data privacy and security, but do not yet mandate 'digital sandboxes' or 'spending limits' for AI agents, which are the equivalent of physical security guards on factory robots.

Faced with these challenges, regulators are beginning to change their strategy. In early 2026, we will see new discussions on:

- Dynamic documentation: Requiring agents to maintain a 'black box' flight recorder for each call and tool-related decision.
- Auditability of agents: Ensure an agent can explain why they took a specific action, not just what it generated.

- Emergency switches: Mandatory emergency stop protocols for autonomous systems.

The geopolitical race for 'computer security'

The analogy that 'computing is the new oil' highlights the deep link between a nation's energy capacity and its technological competitiveness. The immense energy demands of AI data centres mean that the nations that control access to reliable energy and supercomputing infrastructure will wield the same kind of power as those that once dominated energy supplies. This context elevates a nation's ability to modernise its grid, expand low-carbon energy sources, and improve resource efficiency from a sustainability goal to a national security imperative. Indeed, the push for 'sovereign AI' — the push by nations to develop their own AI infrastructure, models, and data within their borders — is a direct response to this, as countries seek to reduce their exposure to geopolitical risk by developing their own national AI capacity.

Unsurprisingly, by 2026, sovereign AI has become a major driver of change in the energy sector. This trend is transforming the relationship between technology and energy, moving from one of 'consumer and supplier' to a deeply integrated strategic alliance. Here's how sovereign AI is impacting the sector:

The energy 'entrance fee' for sovereignty

Nations like the UAE, Saudi Arabia, and India are discovering that sovereign AI is as much about energy policy as it is about technological policy. Unlike the global cloud (where data centres can be located anywhere with inexpensive power), Sovereign AI requires data centres to be built locally. This puts enormous pressure on national grids, which were not designed for such high-density loads. AI training also requires 'always available' energy. This is revitalising interest in nuclear power, specifically in small modular reactors, which provide constant, carbon-free power for sovereign data clusters, whilst driving a renewed interest in commercially developing fusion power.

'Smart grids' as a sovereign asset

To manage the massive energy spike caused by localised AI, countries use that same AI to manage their energy grids. Sovereign AI models are being trained based on local weather and consumption patterns to optimise the network in real time. This reduces energy waste from wind and solar farms. By controlling the AI that manages the grid, nations protect their critical energy infrastructure from external cyber interference, a key pillar of sovereignty.

Change in energy investment

There is a trend towards 'AI growth zones', geographical areas where energy infrastructure is specifically accelerated for AI. In this context, governments and local state entities no longer only buy energy, but now co-invest in high-voltage transmission lines and on-site generation (such as carbon-capture gas turbines) to ensure that their sovereign models are never disconnected. Sovereign wealth funds, such as PIF in Saudi Arabia or Mubadala in the UAE, are investing billions in 'green' energy projects specifically to boost their national AI ambitions, effectively linking the future of their oil-based economies with an AI future based on renewable energy.

Ultimately, sovereign AI is transforming the energy sector from a quiet utility to a strategic national security frontier. As countries move away from global dependence on the cloud and toward localised, high-density infrastructure, the power grid is no longer just a 'supplier' but the backbone of a nation's digital autonomy. In this new scenario, the success of a country's AI ambitions will be measured not only by the sophistication of its algorithms but by its ability to guarantee a stable, sustainable, and sovereign electricity supply, making the search for intelligence a permanent catalyst for the global energy transition.

Strategic Recommendations

The way forward for organisations involved in energy is not a simple adoption plan, but a multifaceted strategy that views AI as a foundational capability to be developed and not simply a product to be purchased. Success depends on a holistic approach that integrates technology, talent, and strong governance right from the start.

Technology and innovation strategy

Organisations should prioritise high-impact use cases that offer a clear return on investment (ROI) and scalability, such as predictive maintenance, renewable energy forecasting, and smart grid optimisation. This approach allows small-scale pilot programs to test feasibility before scaling them up. In addition, it is critical to promote and invest in energy-efficient hardware and AI-optimised cooling solutions to address the AI energy paradox, ensuring that AI's net impact is positive.

Organisational and talent strategy

The significant talent gap must be addressed through a strategic workforce plan that prioritises the acquisition and development of dual domain expertise in both AI/data science and energy-specific operational technology (OT). The most successful AI deployments in the energy sector involve building a dedicated data science team and fostering a culture of collaboration with business stakeholders, demonstrating the importance of an integrated approach to technology and talent.

Governance and risk management

A comprehensive AI governance framework is essential to ensure regulatory compliance, ethical use, and robust risk management from development to implementation. This framework should include strict data privacy and cybersecurity protocols to protect against new AI-driven threats such as data poisoning and adversarial attacks. Organisations must also actively work to mitigate algorithmic bias and ensure transparency and accountability in all AI-driven decisions.

Collaboration and ecosystem development

Finally, organisations must collaborate with regulators, academia, and industry peers to shape policy and share best practices. By engaging in public-private partnerships, the energy sector can help accelerate the secure development and deployment of next-generation technologies whilst ensuring that AI serves the public interest and contributes to a more resilient and sustainable energy future for all.

Resources and references

'AI and Energy Security' — International Energy Agency (IEA), 2025/2026.

'AI Drives a Transformative Wave in Global Data Centers' — JLL / Carbon Credits, January 2026.

AI Energy Calculator, '5 Ways to Reduce Your AI Model's Energy Consumption Without Sacrificing Performance', Sep 05, 2025 by AI Energy Team.

AI Energy Calculator, 'The Future of AI is Green: Emerging Technologies for Energy-Efficient Machine Learning', September 08, 2025 by AI Energy Team.

'AI in Energy: From Experimentation to Strategic Imperative' — Mesh-AI / Enlit Europe, Dec 2025.

'AI in the Oil and Gas Industry: From drilling optimization to market prediction'.

'AI-driven operations forecasting in data-light environments', by Jorge Amar, Sohrab Rahimi, Zachary Surak and Nicolai von Bismarck, February 15, 2022, McKinsey & Co.

'Anomaly Detection in a Smart Industrial Machinery Plant Using IoT and Machine Learning,' by Angel Jaramillo-Alcazar, Jaime Govea and William Villegas-Ch, School of Cybersecurity Engineering, Faculty of Applied Sciences Engineering, Universidad de Las Americas, Quito 170125, Ecuador October 7, 2023.

April 22, 2024.

Author: Shaswat Dixit, Senior Solution Architect, Industry NeXT and IoT, HCLTech

By Amber Jackson June 09, 2025.

by Daniel Icaza Alvarez, Fernando González-Ladrón-de-Guevara, Jorge Rojas Espinoza, David Borge-Diez, Santiago Pulla Galindo and Carlos Flores-Vázquez. Energies 2025, 18(6), 1523; (This article belongs to the Special Issue Intelligent Concepts for the Modelling, Optimization and Control of Smart Energy Systems).

'Critical Infrastructure Facing Cyber Surge: The Rise of Autonomous Adversaries' — SC Media, January 2026.

Data Centre Magazine, 'Google to Back TAE Technologies Nuclear Fusion Energy'

'Energy and AI' (Special Report) – International Energy Agency (IEA), April 2025.

'Energy in the Age of AI: Key Trends for 2026' — Energy Management Institute, December 2025.

'Futureproofing Cyber Regulation: The NIS2 and Cyber Resilience Act Era' — Ofgem, January 2026.

'Geological Everything Model 3D: A Promptable Foundation Model for Unified and Zero-Shot Subsurface Understanding"by Yimin Dou, Xinming Wu, Nathan L Bangs, Harpreet Singh Sethi, Jintao Li, Hang Gao, and Zhixiang Guo, ARXIV, https://arxiv.org/html/2507.00419v1

Google Blog, 'Our latest bet on a fusion-powered future,' Jun 30, 2025.

Google Deepmind, 'Bringing AI to the next generation of fusion energy,' The Fusion Team, October 16, 2025 Science.

'How AI Can Accelerate the Energy Transition, Rather Than Compete With It' – World Economic Forum (WEF), November 2025.

'Meta's Energy Dilemma: Powering the AI Future' — Harvard Business School (HBS), Revised Nov 2025

Nucnet.org, 'Google Signs Deal to Buy Fusion Energy From Bill Gates-Backed Nuclear Startup,' By David Dalton, 2 July 2025.

'Outlook 2026: The Algorithmic Arms Race for Energy' — Petroleum Economist, December 2025.

'Physical AI: Paced Adoption in Asset-Heavy Sectors' — Applied AI Pulse, Sep 2025.

ShopHatch, Hardware's New Horizon: Powering AI, Sustainability, and the Edge in 2025, July 2025.

SIngularityHub, Hugging Face Says AI Models With Reasoning Use 30x More Energy on Average by Edd Gent, Dec 15, 2025.

'Sovereign AI and Air-Gapped Security in the Energy Sector' — Google Cloud Transform, January 2026.

'Strategic Roadmap for Digitalisation and AI in the Energy Sector' — European Commission, Jan 2026.

Subsurface Energy and Environmental Systems (SEES), 'Inverse Modelling and Uncertainty Quantification,' Mork Family Department of Chemical Engineering and Materials Scien.ce, USC University of Southern California

Technology Magazine, 'Why is Google Investing in Nuclear Fusion With TAE?', By James Darley, June 06, 2025.

'The AI-Energy Nexus: The Atomic Imperative' — Innovation News Network, November 2025.

'The AI-Energy Nexus: The Atomic Imperative for Sustainable AI' – Purdue University / Innovation News Network, November 2025.

The Chosun Daily, 'AI Simplifies Plasma Control for Nuclear Fusion' by Kang Da-eun, Published 2025.10.23.

'The Evolution of AI Applications in the Energy System Transition: A Bibliometric Analysis of Research Development, the Current State and Future Challenges'

'Top 10: AI Applications in Energy 2025' – Energy Digital, November 2025.

UNESCO, 'Green Digital Transformation", Advancing sustainable and energy-efficient AI to power an inclusive, right-based digital future.

UNESCO, Press release, 'AI Large Language Models: new report shows small changes can reduce energy use by 90%', 8 July 2025, Last update:9 July 2025.

World Economic Forum, Energy Transition, How on-device AI can help us cut AI's energy demand, Mar 7, 2025.

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