PCIC ENERGY : THE AI PARADOX FOR ENERGY

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Abstract Generative Artificial Intelligence (AI) is rapidly transforming every industry. The energy sector, with its inherent complexity and data intensity, is particularly well-positioned to benefit from AI applications that enhance efficiency, reduce costs, and enable the production of cleaner energy.

Yet, while the advantages of AI in improving production, optimization, and predictive maintenance are significant, its adoption also brings a less discussed challenge: the substantial increase in energy demand required to power AI models and the data infrastructure behind them.

For electrical engineers and energy professionals, this creates a paradox: AI simultaneously acts as both a driver of energy efficiency and a consumer of considerable energy resources.

The objective of this paper is to explore this “AI–Energy Paradox” by assessing the balance between the gains AI delivers and the costs it imposes on the energy system.

The paper will be structured in four sections:

1. **Definition and Use Cases** — Introduction to AI, with a focus on generative capabilities and concrete applications across the energy sector.

2. **Production Benefits** — Quantitative estimation of efficiency improvements, production increases, and cost savings enabled by AI.

3. **Energy Demand Impact** — Calculation and estimation of the additional electricity demand driven by AI workloads and infrastructure.

4. **Net Assessment** — Comparative analysis weighing AI’s energy savings and productivity gains against its energy consumption, with implications for strategy and sustainability in the energy sector.

Index Terms — PCIC energy Paper Format, Writing instructions, Style requirements.

I. INTRODUCTION

Artificial intelligence (AI) moved from a niche technological subject for science lab, to a global trend when it entered everyday academic life after widely publicized cases of students using AI tools to cheat. One of the most influential moments came when Harvard faced incidents involving students submitting AI-generated work, sparking intense debate across universities worldwide. This case did not merely highlight academic misconduct; it exposed how powerful and accessible AI had become. As a result, AI shifted from being viewed as an emerging innovation to a disruptive force capable of reshaping education, ethics, and professional standards. The Harvard case became a catalyst, accelerating public awareness and pushing AI into mainstream conversation.

It is strongly recommended that the rough draft paper be prepared using the format described in this document.

II. DEFINITION AND USE CASES

A. Definition

Artificial Intelligence (AI) is a branch of computer science that focuses on creating machines (or models) and systems capable of performing tasks that typically require human intelligence.

These tasks include learning from experience, recognizing patterns, understanding language, solving problems, and making decisions.

AI systems work by using algorithms and large amounts of data to identify patterns and improve over time. For example, recommendation systems on streaming platforms, virtual assistants, and self-driving cars all rely on AI to function effectively. Over time, AI has evolved into an umbrella term that includes several distinct concepts, such as big data, machine learning, and generative AI.

Big data, for example, refers to extremely large and complex datasets that cannot be easily processed using traditional methods. It is not a form of intelligence itself, but rather the raw material that fuels AI systems. AI uses big data to detect patterns, make predictions, and improve performance. Without sufficient data, many AI systems would struggle to function effectively.

Machine learning (ML) is also a sub-topic of AI that focuses specifically on enabling models to learn from data rather than being explicitly programmed. Instead of following fixed rules, ML models identify patterns in data and adjust their behavior over time. For example, a spam filter improves by learning from previously labeled emails. In this sense, machine learning is one of the main techniques that makes modern AI possible

There are different types of AI, ranging from narrow AI, which is designed for specific tasks (like voice recognition), to more advanced concepts such as general AI, which aims to perform any intellectual task a human can do.

Although general AI is still largely theoretical, narrow AI is already being used in everyday life and in professional life. As technology continues to evolve, AI is playing an increasingly important role in our industries, beyond writing emails, and transforming the way we live and work.

Traditional AI mainly analyzes data to recognize patterns, make predictions, or support decisions. At the opposite of Generative AI, that creates new content such as text, images, or music based on what it has learned. Usually, we consider traditional AI answers questions about data, while generative AI produces entirely new outputs from it.

B. Core Pillars of Artificial Intelligence

As mentioned already, Artificial Intelligence (AI) is a broad umbrella that includes many branches and concepts beyond just big data, machine learning. Each of these areas focuses on a different aspect of making machines intelligent.
Here are some of the most important ones:

1. **Deep Learning**
   Deep learning is specific branch of machine learning that uses multi-layered neural networks (like the human brain) in black-box to process complex data like images, audio, and text. It's what powers most modern AI breakthroughs, including generative AI.

2. **Natural Language Processing (NLP)**
   This focuses on enabling machines to understand, interpret, and generate human language. It's used in chatbots, translation tools, and voice assistants.

3. **Robotics**
   Combines AI machines with physical machines (robots) so they can interact with the real world. Robots can use AI to navigate, manipulate objects, or perform tasks autonomously.

4. **Computer Vision**
   This allows machines not only to see but to interpret visual information from the world, such as images and videos. It's used in facial recognition, medical imaging, and autonomous vehicles.

5. **Planning and Search Algorithms**
   These area goal is to figure out sequences of actions to achieve specific complex goals. A good example is route planning in GPS navigation systems.

6. **Expert Systems**
   Early AI systems designed to mimic the decision-making ability of a human expert. They use rules and knowledge bases rather than learning from data.

7. **Reinforcement Learning**
   A type of machine learning where an agent learns by interacting with an environment and receiving rewards or penalties. It's widely used in game AI and robotics.

8. **Knowledge Representation**
   How information and relationships are structured so that machines can reason about them (e.g., graphs, ontologies).

9. **Data Mining**
   The process of discovering patterns and insights from large datasets. This is the applicable case of both Big Data and Machine Learning.

10. **Edge AI**
    AI that runs directly and physically on decentralized devices (like smartphones or IoT devices) instead of relying on cloud computing, enabling faster and more private processing.

11. **Multi-Agent Systems**
    Systems where multiple AI agents interact, cooperate, or compete to solve problems.

C. Uses Cases

AI is applicable in a variety of task in the energy industry, but what is going to interest us in this paper is not about writing email faster. When looking at our industry it seems inevitable AI is going to transform the way we work, below is a list of the most important use cases identified as of today technology.
For each use case, we will try to focusing on the original challenge, then what AI is changing, and finally the gains.

- Exploration & drilling

Seismic interpretation
Traditionally, geophysicists manually interpret with models giant seismic dataset, which is slow and subjective. AI automates pattern detection in seismic images, improving consistency and speed. A little bit like AI is getting better at detecting/interpreting radiographies than doctors.
Gains: faster discovery cycles, reduced exploration costs, less false positives and fewer missed opportunities.

Reservoir characterization
Estimating subsurface properties is complex and uncertain due to limited data. AI integrates geological, seismic, and well data to create more accurate reservoir models.
Gains: better reserve estimates, improved recovery rates, and reduced uncertainty at production.

Exploration risk prediction
Drilling decisions often rely on incomplete datasets and expert judgment. AI uses massive historical drilling outcomes to predict success probabilities more objectively.
Gains: fewer dry wells, better capital allocation, lower financial risk.

Drilling optimization
Drilling parameters are usually adjusted manually or with simple rules of thumb. AI optimizes drilling parameters in real time based on downhole data and conditions, based on historical data and combination of the instrumentation.
Gains: faster drilling, reduced non-productive time, lower operational costs.

Drilling anomaly detection
Hazards like kicks or stuck pipes are often detected late, too late. AI identifies subtle patterns and little noises signaling early-stage anomalies.
Gains: improved safety, fewer accidents, reduced downtime and repair costs.

- Operations & production

Predictive maintenance
Maintenance is often reactive or scheduled, leading to unexpected failures or unnecessary servicing. AI and machine learning predicts failures using sensor data trends. And can go one step further by forecasting failure.
Gains: reduced downtime, longer equipment life, lower maintenance costs.

Production forecasting
Forecasting production is complex and often made manually and as such is quite inaccurate. AI can model dynamic reservoir behaviors using real-time and historical data.
Gains: better planning, optimized output, improved revenue predictability.

Well optimization
Operators rely on experience and gut feelings to adjust well settings. AI can identifies quickly and without large infrastructures optimal operating conditions continuously.
Gains : increased production, reduced energy use, improved efficiency.

Real-time asset monitoring
Monitoring large, distributed assets is difficult with traditional systems. AI detects anomalies across thousands of data points instantly.
Gains: early issue detection, reduced failures, improved reliability.

Process optimization
Industrial processes are complex and often suboptimal given the operating point and external factors. AI continuously optimize parameters to maximize efficiency based on more datasets and external factors. AI can also goes as far as finding new operating points.
Gains: higher yields, lower energy consumption, reduced waste.

- Project Stages

Concept selection and planning
Choosing the best project concept involves many uncertain variables or expensive detailed engineering. AI can evaluate multiple scenarios quickly and precisely using data-driven insights and historic of projects.
Gains: better and faster decisions, reduced project risk, improved ROI.

Cost and schedule forecasting
Projects often suffer from overruns due to forecasting mistake. AI learns from past projects to predict delays and cost risks. It is not bullet-proof but can alert about missing pieces of the puzzle.
Gains : more accurate budgeting, less overruns, better project control.

Engineering design support
Engineering design is time-consuming and iterative. AI can suggest optimized designs or even pre-design units and process by sourcing from past projects. AI can also pre-calculate all data to by automating documents integration from the supply chain.
Gains: faster design cycles, reduced engineering effort, improved designs.

Procurement and supply chain
Supply chains are complex and prone to inefficiencies due to the volume of suppliers. AI is used to optimize sourcing, inventory, and logistics as well as planning.
Gains: reduced costs, fewer delays, better inventory management.

- Environment

Emissions monitoring
Tracking emissions manually is almost impossible and often delayed. AI enables continuous monitoring, scouting from multiple datasets, comparison between emissions standards and live accounting of carbon emissions.
Gains: better compliance, reduced environmental impact, improved reporting accuracy.

Leak detection
Leaks are often detected late using detectors. AI can identify anomalies and leaks from the process directly, drop in pressure or satellite image automatically.
Gains : reduced product loss, lower environmental damage, faster response.

Spill detection and response
Spill detection relies on human observation or delayed reporting. AI can detect spills in real time using satellite imagery and sensors.
Gains : quicker containment, reduced cleanup time, minimized damages.

Energy efficiency optimization
Energy use is often inefficient due to static operating conditions. AI can dynamically detect opportunities and optimize energy consumption.
Gains : lower costs, reduced emissions, improved sustainability.

Water management
Managing water injection and treatment is complex, relatively unstudied, and resource-intensive. AI can optimize usage and treatment processes.
Gains : reduced water consumption, lower treatment costs, improved efficiency.

- Safety

Incident prediction
Safety risks are often identified only after incidents occur. AI analyzes patterns to predict potential hazards in advance.
Gains: fewer accidents, safer operations, reduced liability.

Worker safety monitoring
Monitoring workers manually is limited and inconsistent. AI via cameras can detect unsafe behaviors or missing protective gear.
Gains: improved compliance, fewer injuries, stronger safety culture.

Hazard detection
Dangerous conditions such as gas leaks, overheating, pressure issues, may go unnoticed. AI could detect

abnormal signals instantly and prevent any accident or warn people of the area.
Gains: early intervention, reduced catastrophic failures, improved safety.

Remote inspection (drones & robots)
Human inspections in hazardous areas are risky and costly. AI-powered robots and drones can perform inspections safely.

Gains: reduced human exposure, lower inspection costs, better data collection.

III. PRODUCTION BENEFITS

A. *Equinor – Predictive maintenance Using Machine Learning*

Predictive maintenance in oil and gas relies on supervised and unsupervised machine learning models applied to high-frequency industrial IoT (IIoT) data streams.
Shell applied Machine Learning models to different datasets of time-series to detect anomality by analyzing gradient boosting models, and deep neural networks.

Those were trained on historical failure events and real-time SCADA data (e.g., vibration spectral analysis, thermodynamic signals, pressure transients).
The primary challenge addressed was the inability of traditional preventive maintenance strategies to capture stochastic failure modes, particularly in complex rotating equipment.
AI resolves this by identifying latent degradation patterns and multivariate correlations across thousands of sensors, enabling early fault detection.
Since 2020, Equinor has deployed this AI service across more than 5,000 industrial assets, integrating platforms such as C3 AI and cloud-based data pipelines.

For example in Equinor , the Predictive maintenance AI service was installed to monitor over 700 rotating machines with 24,000 sensors across all facilities. This predicts failures and maintenance has improved safety, provided more stable operations, and reduced the risk of sudden shutdowns that can lead to flaring and increased CO_2 emissions. This alone has created value of USD 120 million since 2020 for Equinor

Quantified gains:

- Up to 20–30% reduction in unplanned downtime
- Significant improvements in asset uptime and reliability
- Reduction in maintenance-related operational expenditures

REFERENCES :
[1] "Equinor predicts maintenance requirements for its equipment with the use of machine learning"
Link
[2] "Harnessing volatility: Technology transformation in oil and gas"
Link

B. *BP - Deep Learning for Seismic Interpretation*

Seismic interpretation has been transformed by deep convolutional neural networks (CNNs) and, more recently, transformer-based architectures trained on labeled seismic volumes.
These models perform semantic segmentation of subsurface features, identifying faults, horizons, and stratigraphic discontinuities across petabyte-scale datasets.
Before AI, the traditional bottleneck lied in manual interpretation workflows, which were both time-intensive and prone to interpreter bias. AI models now address this by enabling automated feature extraction and probabilistic subsurface mapping, significantly increasing interpretive consistency.
BP now uses the modern implementations integrate cloud-based HPC infrastructure (e.g., Azure) with AI pipelines capable of ingesting seismic cubes and generating 3D geological models in near real time.

Equinor is also using AI for seismic analysis. With AI, more data can be interpreted, covering more square kilometres and enhancing the overall understanding of an area and of the Norwegian continental shelf. A good geological understanding is key to new discoveries, and this is an important tool. In 2025, 2 million square kilometres were interpreted using the AI tool for Equinor.

Quantified gains:

- Interpretation cycle time reduced from months to weeks or days
- Improved drilling success probability through better reservoir targeting by 35%

Reference :
[3] Four shifts redefining the oil and gas operating model of the future
Link

C. *Aramco - Real-Time Drilling Optimization via Reinforcement Learning*

Drilling optimization systems are based on the increasingly leverage of Reinforcement Learning (RL) technologies as and hybrid physics-informed Multi Levels models to dynamically adjust drilling parameters.
These systems ingest real-time telemetry (MWD/LWD data) and optimize control variables such as rate of penetration (ROP), weight on bit, and mud flow rates.

The core challenge for Aramco was lying in the nonlinear, dynamic nature of drilling environments, where static models fail to adapt to changing geological conditions.
AI introduced closed-loop optimization, continuously learning from feedback signals to maximize drilling efficiency.
Recent developments now include the large-scale AI systems called Aramco's industrial large language model (LLM), which integrates decades of drilling data to accelerate drilling operation decisions.

But not only Aramco is working on the topic. ConocoPhillips applied ML to Eagle Ford drilling data, allowing the model to optimize parameters such as weight on bit, revolutions per minute, and mud properties. Documented outcomes included higher rate of penetration (ROP), fewer motor failures, and measurable cost savings per well.

The AI-enabled autonomous well control system RoboWell was deployed in ADNOC fields, enabling real-time tuning of gas-lift. Resulting in about a 30% reduction in gas-lift consumption, significant reduction in manual interventions, and improved production stability. RoboWell marks a transition from supervisory control toward closed-loop, AI-driven operational tuning

Equinor has published that in the Johan Sverdrup phase 3, AI found a drilling solution that no one had considered, saving the partnership USD 12 million.

Quantified gains:

- Up to 25% increase in drilling speed
- Reduction of non-productive time by up to 50% in some cases
- Lower cost per well & improved operational safety

REFERENCES:

[4] The New Nervous System Inside Saudi Aramco
Link

D. Shell - AI-Driven Process Optimization in LNG Facilities

The challenges across most LNG businesses is that they have large amounts of data that are never analyzed and lack the experience necessary to figure out the right moves to make in a timely manner. Being able to aggregate multi-source data and visualize it all in one area is a game changer.
LNG operations involve highly nonlinear thermodynamic processes governed by complex heat exchange and phase transitions. AI is applied through multivariate regression models, digital twins, and model predictive control (MPC) enhanced with machine learning.
The challenge lies in multi-variable optimization under operational constraints, where traditional control systems cannot simultaneously optimize throughput, energy consumption, and emissions. AI models continuously recalibrate optimal setpoints using real-time process data.
These systems are often deployed as hybrid digital twins, combining first-principles physics models with data-driven ML corrections to improve prediction accuracy.

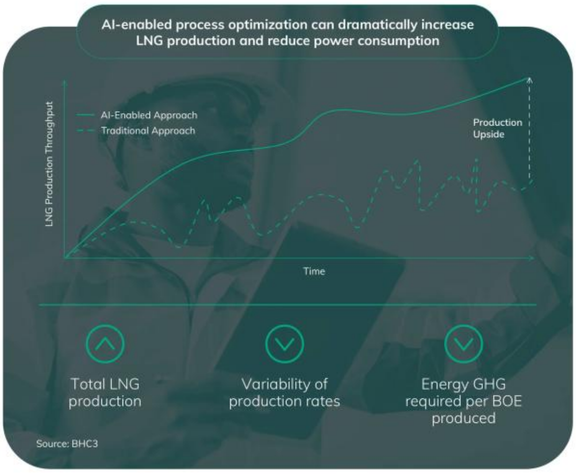

Fig. 1 Gains from using AI in LNG production

One example of how this can work in practice is the Shell Process Optimiser for LNG, which is an LNG module that is built on top of BHC3 AI software.
The Shell Process Optimiser for LNG combines machine learning with process insights and domain expertise to enhance asset production, helping engineers close the gap between current and optimal production by changing operating conditions. This has resulted in a 1% to 2% increase in LNG production.
The module has been made available to other operators as part of the Open AI Energy Initiative (OAI), an open ecosystem of AI-based solutions for the energy and process industry founded alongside C3 AI, Baker Hughes and Microsoft.

Quantified gains:

- 2–5% increase in production efficiency
- Multi-million dollar annual savings through energy optimization and increased production volume
- Reduction in CO_2 emissions via improved process efficiency

REFERENCES :

[5] How Artificial Intelligence Will Help Drive the Future of Energy
Link

E. TechnipEnergies - AI-Augmented Engineering with Industrial LLMs

Engineering workflows are being transformed by large language models (LLMs), generative design algorithms, and knowledge graph–based AI systems. These technologies enable engineers to query vast repositories of technical documentation, simulation data, and historical project records using natural language interfaces.
The primary challenge addressed is the fragmentation of engineering knowledge across siloed systems and documents, which slows decision-making and limits design space exploration. AI resolves this by enabling semantic search, automated reasoning, and generative design optimization.

At Technip Energies, the acceleration of engineering workflows is largely driven by a shift toward data-centric and AI project execution models. Technip Energies integrated AI with unified data platforms and digital engineering environments, enabling seamless access to historical project data and standardized engineering libraries. This approach allows engineers to reuse validated designs, automate parts of the design process, and improve cross-disciplinary collaboration. As a result, engineering cycles are shortened through reduced duplication of work, faster access to information, and improved consistency across project phases.

In parallel, the company is embedding AI directly into engineering tasks to enhance design speed and accuracy. For example, AI models are used to automatically generate material quantities at the tender stage based on historical project datasets, significantly accelerating early-stage engineering and cost estimation. Additionally, AI-assisted design tools (e.g. 3D models) to optimize complex engineering layouts (e.g., cabling or piping), reducing manual effort and iteration cycles while improving design quality. Overall, AI enables a transition from manual, document-centric engineering to automated, data-centric design processes, leading to measurable gains in engineering productivity and project timelines.

Quantified gains:

- Up to 30% reduction in engineering time
- Significant acceleration in decision-making
- Improved design quality through large-scale optimization

IV. ENERGY DEMAND IMPACT

A. *Today Energy demand from AI*

Artificial Intelligence has rapidly evolved from a niche computing workload into the fastest-growing electricity demand globally.
The rise of generative AI systems such as ChatGPT, gemini, claude; for large language models, image generation, has triggered an unprecedented expansion of giant data centers.
According to the International Energy Agency (IEA), the global electricity consumption from data centers is approximately 460 TWh in 2024. Today level of electricity consumption is already equivalent of France total consumption; to note France is the 10 largest electricity consumer on the planet.

The primary driver of this increase is the rapid expansion of AI workloads, particularly generative AI models requiring massive computational power for both training and inference. The scaling of AI infrastructure is already affecting grid stability, electricity investment planning, cooling-water demand, and the long term development strategies of both nuclear and natural gas sectors.
Sam Altman, CEO of OpenAI, has publicly acknowledged the growing energy intensity of AI systems while arguing that the long term benefits justify the infrastructure buildout.

In 2025, Altman disclosed one official estimates of energy consumption associated with ChatGPT usage. Stating that a single ChatGPT query consumes approximately 0.34 watt/hour of electricity. Mr Altman compared this amount to operating an oven for roughly one second or powering a highly efficient lightbulb for several minutes.

While the need for lighting and cooking is not to be proven, the question is not easy to answer for AI usage. Behind this number arises the urgency of expanding energy production. Energy is become the key factor of AI scale up, as every major AI company is now increasingly investing in renewable energy, nuclear power, grid-scale batteries, and dedicated gas-fired generation assets to secure long-term electricity supply.

The impact on global power systems is already visible. The IEA projects that the USA alone will account for nearly half of global data-center electricity growth through 2030, while China and Europe follow closely behind. Several regions are now experiencing transmission bottlenecks, delayed grid interconnections, rising industrial electricity prices, and restrictions on new hyperscale data-center developments.

As of 2026, several U.S. jurisdictions introduced restrictions or temporary moratoriums on new AI-related data-center projects because of concerns over electricity availability, grid resilience, and water consumption.
At the same time, major technology firms have begun reassessing climate commitments due to the scale of AI-driven electricity demand. Microsoft reportedly reviewed aspects of its 2030 clean-energy strategy because of the massive power requirements associated with AI expansion.

B. *AI energy demand on track for 2030*

The period between 2025 and 2030 is expected to represent the largest digital infrastructure expansion in modern history. McKinsey & Company estimates that global data-center demand could reach 220 GW by 2030, nearly six times larger than 2020 levels, while cumulative investment could exceed $6.7 trillion globally.

The IEA forecasts electricity demand associated with data centers will rise from approximately 460 TWh in 2024 to more than 1,000 TWh by 2030. Much of this growth will be directly linked to AI workloads, particularly advanced generative AI systems and large-scale model training.

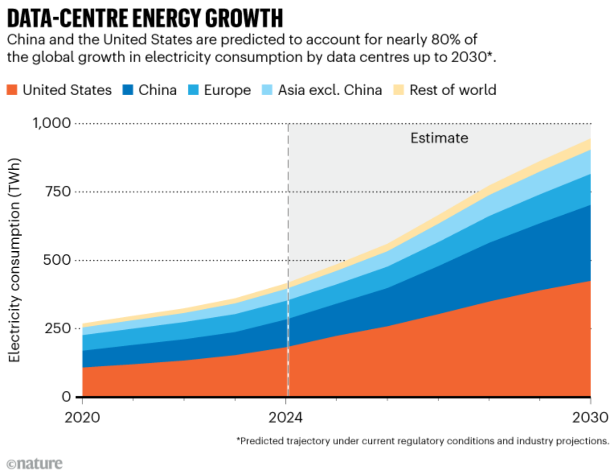

Fig. 2 Energy demand evolution from 2020 to 2030 for Data centers

But contrary to public perception, AI infrastructure is not to be powered exclusively by renewable energy. According to the IEA, the additional electricity required for AI by 2030 will likely come from a diversified mix of renewables, natural gas, nuclear energy, and, in some regions, coal-fired generation. Renewables are expected to provide nearly half of incremental electricity generation, while natural gas will remain essential as a dispatchable backup source capable of supporting the intermittent nature of solar and wind power. Nuclear energy is also expected to play a growing role after 2030 as SMR technology firms seek industrial size and maturity.

This explains why several AI companies are now supporting small modular reactor development, securing long-term LNG and gas-fired power contracts, and investing directly in energy infrastructure.

C. Energy forecast for AI in 2050

By 2050, AI is expected to evolve from a technology-sector issue into a structural component of national energy systems. Academic modelings suggest that AI infrastructure could become a permanent baseload electricity consumer comparable in scale to heavy industry today.

Under moderate growth scenarios, AI infrastructures could account for between 7% and 10% of global electricity demand by 2050. Under more aggressive scenarios involving autonomous systems, advanced robotics, real-time AI services, and widespread industrial deployment, AI electricity demand could exceed that of today's aviation or steel sectors.

One of the most significant consequences of this growth may be the revival of nuclear energy. Technology firms increasingly view nuclear power, small modular reactors, geothermal energy, and dedicated microgrids as essential components of long-term AI expansion strategies. The need for stable, 24/7 carbon-free electricity is pushing those startups toward energy independence and dedicated generation assets rather than reliance on increasingly congested public grids.

The geopolitical implications are also substantial. By 2050, energy availability may become one of the defining factors of global AI competitiveness. Countries with abundant electricity resources, low-cost natural gas for example, advanced nuclear sectors, or large renewable-energy capacity could dominate the next generation of AI infrastructure investments. This dynamic may strengthen the strategic importance of the United States, the Gulf region, Canada, Scandinavia, and nuclear economies.

AI is therefore transitioning from a software problematic into a physical infrastructure one. The next phase of AI competition will depend not only on algorithms, semiconductors, and computing power, but increasingly on electricity generation, grid capacity, cooling infrastructure, and energy security.

V. NET ASSETMENT

The environmental implications of AI expansion remain uncertain because efficiency improvements in hardware and software continue to offset part of the increase in electricity demand. The IEA's base-case scenario suggests that emissions associated with data-center electricity consumption could peak around 2030 if renewable deployment accelerates sufficiently. However, under more aggressive AI adoption scenarios, fossil fuels could still provide up to half of the additional electricity generation required.

A. AI Energy Consumption Vs Energy Savings

The central uncertainty remains whether improvements in AI efficiency will outpace the explosive growth in AI demand. If demand continues to expand faster than efficiency gains, AI could become one of the world's largest new industrial electricity loads.

Artificial Intelligence is set to become a major future electricity burden, but a net assessment suggests that AI could ultimately generate larger energy savings across the global economy than the energy it directly consumes.

According to the IEA, global data-center electricity demand will be roughly 1,000 TWh by 2030, largely driven by AI workloads. This would represent around 3% of global electricity demand by 2030. However, AI applications are simultaneously improving efficiency across power systems, industrial operations, logistics, buildings, and oil & gas infrastructure; and this in percentages higher than 3%.
As detailed before AI is deployed to optimize systems, improve production, reduce costs, raise efficiency, improve uptime, and cut emissions across energy-intensive sectors. Several independent estimates now suggest that AI optimization could reduce global energy consumption by between 5% and 10% across industrial and infrastructure systems by 2040, equivalent to several thousand terawatt hour annually, significantly exceeding the direct electricity consumed by AI infrastructure itself.

D. Oil & Gas Sector as first beneficiary

The oil and gas sector may represent the largest immediate net-positive energy impact of AI deployment. Upstream operations currently generate approximately 4.1 gigatons of CO_2 equivalent emissions annually, representing almost 10% of global anthropogenic greenhouse gas emissions. According to McKinsey, AI can reduce energy intensity and emissions by stabilizing operations, reducing flaring, minimizing downtime, and optimizing equipment performance. Their analysis shows that a 10% increase in production efficiency can deliver approximately a 4% reduction in emissions intensity. In practical terms, this translates into very large energy savings across global upstream operations. Oil and gas assets consume vast quantities of power for compression, pumping, LNG liquefaction, refining, and offshore production. AI optimization of compressors, turbines, pumps, and drilling systems could reduce operational energy demand by 10% across many facilities. In refining alone, where global energy consumption exceeds 8,000 TWh equivalent annually, even a conservative 5% efficiency gain would represent approximately 400 TWh of energy savings per year. This is nearly equivalent to the entire current annual electricity demand of global AI data centers. Additional gains from methane detection, flare reduction, and electrification optimization further increase the net positive balance. AI could reduce approximately 80% of methane emissions coming from oil and gas at no net cost due to operational efficiencies and captured gas value.

E. Long Term Outlook: AI as Both Consumer / Optimizer of Energy

Looking toward 2050, the balance between AI energy consumption and AI energy optimization is likely to become increasingly favorable. While AI data centers may require around 1,000 TWh annually by 2030, the broader application of AI across industrial systems, power grids, transportation networks, and heavy industry could generate energy savings several times larger.

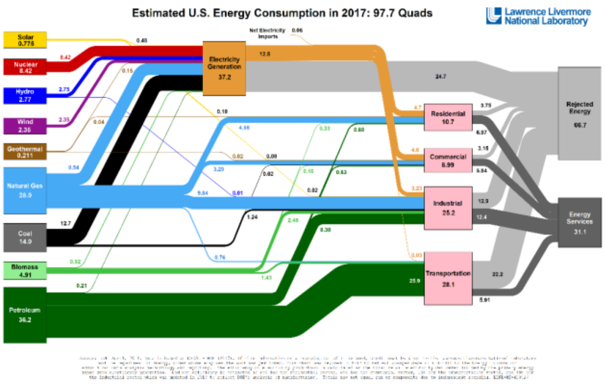

Fig. 3 10 years ago, 67% of the energy produce was wasted in the process of its consumption.

By 2050, AI may therefore evolve into both a major electricity consumer and one of the world's largest energy efficiency enablers simultaneously. The share of energy being produces but wasted is a large pool of saving AI is going to tape. Today the estimation is that more than 50% of the energy produced is wasted outside of any valuable usage.

The net outcome will likely depend on whether AI deployment prioritizes optimization of physical systems rather than purely computational expansion. Current evidence suggests that although AI infrastructure will significantly increase electricity demand, the cumulative energy savings enabled by AI across heavy industry, oil and gas, logistics, and energy systems could ultimately exceed the direct energy consumed by AI itself by a factor of two to five over the long term.

VI. CONCLUSION

The central challenge for governments and industry over the next quarter century will be balancing AI driven economic growth with decarbonization targets, grid resilience, and affordable electricity supply. As Sam Altman noted, the future of AI may ultimately depend on how quickly the world can scale abundant energy production.

Artificial Intelligence is creating a major energy paradox in this 21st century. While AI infrastructure and data centers are expected to consume enormous amounts of electricity over the coming decades, AI also has the potential to become one of the most powerful energy optimization tools ever developed. Across the oil & gas sector and wider industrial economy, AI is already improving efficiency, reducing waste, optimizing maintenance, lowering emissions, and increasing operational performance.

The long-term balance will also depend on how AI is deployed and powered. If supported by investments in low-carbon power, grid modernization, and industrial optimization, the energy savings enabled by AI could ultimately exceed the electricity consumed by AI itself. AI should therefore be viewed not only as a growing energy consumer, but also as a critical technology for building a more efficient and resilient global energy system.

VII. APPENDIX

- AI : Artificial Intelligence
- SMR: Small Modular Reactor
- TWh : Terra Watt Hours
- IEA : International Energy Agency
- LNG : Liquified Natural Gas

VIII. VITA

Jean Guilhem graduated from the engineering school Supélec Paris with a specialization in Electro-communication. After several experiences in Siemens Oil&Gas and Air Liquide Large Industry working on digital topics, he received a MBA degree from the SDA Bocconi in Milan. Joining 2b1st Consulting in 2018, he is now the CEO of the company pursuing the heritage of expertise in energy and digitalization.
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