CTT
Centre for Trustworthy Technology

# A New Era for Energy: Exploring Artificial Intelligence's Transformative Role

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# Introduction

At this pivotal moment, the world faces a defining challenge in the battle against climate change. We are armed with groundbreaking technologies, poised for transformative action, yet the clock is ticking louder than ever. Our mission is stark: slash greenhouse gas emissions by 45% from 2010 levels.[i] This isn't just a goal; it's a necessity to prevent catastrophic environmental collapse. Alarmingly, the latest Intergovernmental Panel on Climate Change Assessment Report delivers a sobering wake-up call. Instead of decreasing, global emissions are projected to surge by 10% over the next eight years, using 2010 as a baseline.[ii] This isn't just a setback; it's a clarion call for urgent, decisive action. The future of our planet hangs in the balance, and the time to act is now.

The United Nations Climate Change Conference held in 2023, COP28, presented a crucial platform for world leaders to take cognizance of our climate change predicament and commit to a strategic vision to navigate a resilient future. At the conference, the UAE consensus has called for tripling of renewable energy capacity and doubling of energy efficiency by 2030.[iii] Energy consumption is the primary contributor to GHG emissions, accounting for 76% of global emissions.[iv] In the United States, power outages have surged by 78% in the last year, with its annual costs estimated to be between $10 and $100 billion.[v] In this context, it is crucially important to enhance the suitability of our energy infrastructure to be more efficient, efficacious, and equitable to advance the sustainability mission.[vi]

Amongst the diverse array of solutions and strategies proposed for this environmental transition, the prominent role of Artificial Intelligence (AI) is particularly noteworthy.[vii][viii] AI holds the promise of profoundly influencing the energy sector, offering key insights that could contribute to a 5% to 10% reduction in global greenhouse gas emissions by 2030.[ix] Embracing technological advancements facilitated by AI in the energy sector, is key to making significant strides along this consensus. In alignment with this vision, the energy and power sector invested $3.103 billion in AI in 2021, a figure expected to exceed $14.257 billion by 2028.[x] Approximately 92% of companies in the Energy and Utilities sector have embraced or plan to integrate AI within the next two years, seeking competitive advantages.[xi]

AI boasts a wide array of impactful applications within the energy sector, ranging from enhancing the integration of renewable energy into power grids to advancing predictive maintenance of the infrastructure and strengthening grid cybersecurity. Its role is pivotal in facilitating the shift towards smarter, more decentralized energy systems. Additionally, AI is empowering consumers towards becoming independently power sufficient, aiding in modeling new age energy infrastructure, and playing a crucial role in the discovery of innovative materials for clean energy technologies. Its use in the energy sector is building inspiring use cases, emphasizing its potential to drive the global transition towards a more sustainable, efficient, and equitable future.

In the past seven years, we've witnessed a remarkable trend: investments in renewable energy have not just matched but consistently surpassed those in fossil fuels, signaling a transformative shift in the energy landscape.[xii] As AI becomes increasingly integral to the energy sector, it's imperative to foster a transition that is conscientious, responsible, and trustworthy.

# Building Blocks for AI in Energy

Data science establishes a critical base for analyzing and interpreting data in the realm of using AI in the energy sector. This foundational work is further expanded upon by machine learning which utilizes data provided to uncover patterns and forecast future trends.[xiii] Additionally, deep learning, a specialized branch of machine learning, employs artificial neural networks and extensive datasets to generate accurate predictions. In the context of the energy sector, the core objective of digitalization is the transformation of data into valuable insights. AI provides a crucial pivot for this endeavor[xiv] when meticulously architected to facilitate a range of critical functions, including predictive analysis, forecasting, extensive processing of big data, data visualization, as well as the management and optimization of the power grid. This process can be broadly delineated into five distinct processes:

- **Data Collection:** The initial phase where data is gathered from various sources.
- **Data Storage:** This step involves securely storing the collected data for subsequent analysis.
- **Data Pre-processing and Cleansing:** Data is refined and cleaned to ensure accuracy and reliability.
- **Machine Learning and Model Training:** At this stage, AI algorithms are applied, and models are trained to interpret the data.
- **Results Triggering Action:** The final process where the analyzed data is used to make informed decisions.

Each of these stages plays a pivotal role in ensuring the AI infrastructure operates effectively, supporting the energy sector's evolution towards greater efficiency and intelligence.

## Data Collection

Data is often collected through a sensor network comprised of smart meters, grid sensors, environmental sensors, and other tools that aggregate real-time metrics critical to the energy infrastructure. These sensors are designed to track voltage and current, temperature, and power quality while identifying potential risks and energy waste and advising maintenance schedules.[xv] While these sensors come in various formats, they share common traits such as real-time monitoring, Internet of Things (IoT) connectivity, and the ability to collect different data formats. Wireless Sensor Networks (WSNs) are critical in optimizing for data in energy infrastructure, particularly in the renewable energy sector.[xvi] WSNs are built upon:

### Wireless Communication Protocols

WSNs mostly use Zigbee and Long-Range Wide Area Networks (LoRaWAN) as wireless protocols. Zigbee is low-power and preferred for short-range communications in smart grids.[xvii] Meanwhile, LoRaWAN is suitable for long-range wireless communications that require sensor networks for large energy infrastructure projects.[xviii] While Bluetooth is a wireless communications protocol commonly used in various wireless IoT devices, it may not be appropriate for WSNs because it requires, on average, higher power consumption despite having limited short-range communication and scalability.

### Mesh Networking

Mesh networking allows sensors to transmit information directly to each other via a cellular radio network, enabling broader coverage and higher security.[xix]

### Security Protocols

The specific security protocols for WSNs are subject to the requirements of the application, but they often include symmetric encryption, public key infrastructure (PKI), key management protocols for distributing and updating cryptographic keys, secure routing protocols, and data authentication processes.[xx]

### Middleware

WSNs would require middleware for communications (such as message brokering or routing protocols), data management (for data aggregation, storage, and querying), energy management (to optimize energy consumption), time synchronization, and fault tolerance.[xxi]

## Data Storage

AI necessitates computation on enormous datasets with scalable and diverse data types, particularly in the energy sector. Data storage solutions may combine a few of the following: data lakes, data warehouses, cloud storage, distributed storage systems, data versioning or metadata management, and data compression. Data lakes typically store raw and unstructured data from node sensors while data warehouses store structured and processed data, including aggregated datasets from multiple sources within the energy infrastructure[xxii] Once datasets are ready to be trained for AI models, they may move to cloud servers, which are equipped to train and run AI algorithms with high data volume. For example, power plant sensors collect raw data on temperature, pressure, and vibration, which are stored in data lakes. Meanwhile, grid sensors pick up voltage and current levels at various points of the electrical grid and store this information in data lakes. The raw data points from the power plant sensors and the grid sensors are aggregated into a dataset and retained in data warehouses. Finally, the aggregated data is moved to cloud servers, where the data is trained and used to make energy consumption forecasts and other inferences based on the aggregated sensor data.[xxiii]

## Data Preprocessing and Cleansing

Sensors will collect raw data with noise, outliers, and other errors that will lead to incorrect interpretations of the datasets when the data is not correctly "cleansed." Data cleansing refers to data quality assurance procedures that remove dataset errors before analysis. The cleansing process may include:

### Normalization

This data pre-processing method scales the dataset to a standardized range to prevent models from giving too much weight to specific features in the set.

### Feature Engineering

Data scientists may combine various features to represent a more inclusively representative or insightful feature. In these cases, new features are introduced to the model to boost the model's accuracy. Features can also be reduced to eliminate any irrelevant information that may cause model bias.

### Temporal and Spatial Alignment

Time-series data is critical to the energy sector. Raw datasets sometimes need to be synchronized in time and space contexts. Temporal alignment aligns datapoints from various periods. Meanwhile, spatial alignment refers to organizing data based on geographical location.

### Special Care with Categorial Data

Many machine learning algorithms, like logistic regression, support vector machines, and neural networks, require categorical variables to be re-classified before they can be analyzed appropriately within a dataset of primarily numerical data. Categorical variables represent non-numerical values, like "yes" or "no", and must be re-classified into numerical representations to allow for an accurate representation of the value. These variables can be re-classified by creating a dummy/binary variable 0 to represent a "yes" and 1 to represent a "no".

## Machine Learning and Model Training

Finally, once the data is collected and prepared for machine learning, there is a need to choose and apply an appropriate model to draw accurate, insightful, and valuable results. Some of these models could be:

### Parametric and Semiparametric Regression Models

In the energy sector, different types of regression models are used depending on subject of analysis and the relationships between its multiple facets. When the relationship between the response and all explanatory variables is clear, parametric regression models are employed. However, if the relationship is only partially understood — clear for some variables but uncertain or complex for others — semi-parametric regression models are used.

In situations where the relationship is entirely uncertain or nonlinear, nonparametric regression models are the preferred choice in analyzing complex patterns.

Parametric regression, such as a linear regression model, helps identify associations between features extracted from the dataset. These regressions are generally the most popular and simple and are thus commonly used. For instance, these may be helpful to analyze associations between time-dependent variables and other variables like temperature or economic indicators. These regression models may also be applied to track associations between new interventions and asset performance, thereby measuring the effectiveness of new applications. However, it is important to note that regression models are intended to identify associations between variables and cannot conclude causation by their results.[xxiv xxv xxvi]

Semi-parametric models blend parametric and non-parametric approaches, offering adaptability in statistical modeling, especially in the energy sector.[xxvii] These models aren't confined to a fixed functional form, allowing them to handle various data types more effectively. A key application in the energy sector is load forecasting, where they navigate complex, non-linear relationships to predict energy demand accurately.[xxviii] Their main advantage is flexibility, making them ideal for modeling the dynamic and often unpredictable scenarios in the energy sector, where straightforward relationships between variables are rare. This ability to manage non-linear relationships without a predefined structure makes them highly valuable for understanding and forecasting in the energy industry for varied analysis.[xxix xxx]

## Decision Trees and Random Forests

These methods are designed to analyze more complex relationships than simple parametric regressions because they combine consequential decisions to formulate an eventual prediction. The easiest way to understand this model is by picturing a tree with branches that form as a decision is made, and each of those branches leads to differing outcomes. These models aid grid optimization by recommending grid parameter adjustments based on real-time data. Decision trees are also commonly used in forecasting, including predicting energy consumption, and conducting risk assessments.[xxxi xxxii xxxiii]

## Support Vector Machines (SVM)

SVMs are generally employed for classification and learning patterns based on models that train through historical data. In the context of energy, SVMs may be used to learn patterns associated with the production, maintenance, and distribution of energy channels. As patterns are understood, SVMs may assist in detecting faulty equipment and other anomalies within the infrastructure.[xxxiv xxxv xxxvi]

## Neural Networks

Neural networks are models that intend to emulate our current understanding of human brain architecture. They are designed to perform various tasks, including classification, regression, and pattern recognition. It is used in many aspects of energy infrastructure. For example, neural networks have been applied to diagnostics, forecasting, grid control, and risk assessment. The last few years have made neural networks a popular tool to price electricity as well.[xxxvii xxxviii xxxix xl]

# AI in Action:

## Pioneering Applications Transforming the Energy Sector

Modern power systems have evolved from a traditional model where energy flowed one-way from centralized power stations to a more complex framework. In this new system, electricity moves in multiple directions between distributed generators, the grid, and consumers.[xli] This complexity increases with the addition of numerous grid-connected devices, like electric vehicle (EV) charging stations[xlii] and residential solar installations,[xliii] making electricity flows less predictable. This changing landscape requires a stronger exchange of information and more advanced tools for planning and operating power systems in such a dynamic environment.

The transformation of the energy sector brings a range of opportunities, particularly with the current shift towards renewable energy. AI is emerging as a crucial facilitator in the evolving, data-intensive, sustainability seeking energy sector, offering essential capabilities to enhance operational performance and efficiency.[xliv]

The major use cases it is facilitating in the energy sector can be highlighted as:

### Predicting Demand and Supply

AI is aiding in balancing the supply and demand of renewable energy, a sector marked by variability. Its ability to predict and align the intermittent nature of sources like solar and wind power with fluctuating demand optimizes the economic use of renewables, easing their integration into the power grid.[xlv xlvi xlvii] For example, by forecasting wind energy output using weather data and turbine locations, it's possible to synchronize energy-intensive activities with peak renewable production, reducing reliance on external power sources.[xlviii]

### Predictive Maintenance of Energy Infrastructure

AI-driven predictive maintenance systems use machine learning algorithms to analyze large amounts of data from various sources, such as sensors, and to detect patterns that can indicate potential problems. By monitoring and analyzing data from the equipment, AI can detect anomalies that may indicate a need for maintenance or repair. This allows companies to identify and address problems before they become more serious, reducing downtime and costs associated with unplanned maintenance.[xlix]

## Protecting the Grid

The International Energy Agency has noted a significant and rapid increase in cyberattacks targeting utilities since 2018, with these incidents reaching particularly alarming levels in 2022.[l] Recent cyberattacks in the electricity sector have led to the disabling of wind farm remote controls, disruption of prepaid meters, and repeated data breaches, compromising client personal and financial information.[li] The forms of attack are becoming increasingly varied and sophisticated.[lii] Energy companies are increasingly deploying AI technologies to safeguard their grids against cyber threats. This proactive approach involves using AI to continuously monitor and analyze network activities, enabling the detection of anomalous behavior that could indicate a cyberattack.[liii liv] Unlike traditional cybersecurity methods, which mainly defend against known threats, AI-driven systems can identify and responding to new, previously unseen types of cyberattacks.[lv lvi] By leveraging AI, energy companies can not only enhance their defensive capabilities but also ensuring the reliability and security of their power grids, which are essential for both everyday operations and national security.

## Smart Microgrids – Enabling ‘Prosumers’

A smart grid merges energy distribution and digital communication, enabling two-way electricity and data flow, thus improving utility efficiency in electricity generation, transmission, and distribution, and helping consumers better manage and track their energy usage and production, such as from solar panels. Smart grids are increasingly contributing to total energy production operating both independently and in connection with the main grid. Their efficiency hinges on storage scheduling, especially in situations where connection to the larger grid is limited. Renewable energy in microgrids serves not just as a primary source but also as a backup during shortages, reducing disturbances.

The rise of smart grids has given birth to the idea of prosumers. Prosumer, a blend of ‘producer’ and ‘consumer’, refers to entities that both consume and produce energy, usually remaining connected to the grid. These prosumers often generate and store energy. The energy they produce can offset their own energy costs or be sold back to utilities or energy distribution services as surplus.

However, the complexity of smart grids, with their fluctuating renewable energy sources and demand, necessitates more advanced control and protection mechanisms. Traditional methods fall short in managing the variability and dynamism of these grids. Here, AI plays a critical role in enhancing the value of microgrids[lvii] through predictive analysis,[lviii] aligning supply with demand,[lix] maximizing producer revenue while minimizing storage costs,[lx] and enabling rapid response to unexpected demand shifts with real-time storage dispatch.[lxi]

Smart microgrid technology marks a shift from centralized to decentralized energy systems, with distributed management of generation, transmission, and distribution. The integration of AI not only mitigates the risk of energy capacity variability but also aims to elevate Renewable Energy to the level of conventional sources.

# Digital Twin

A digital twin is an AI-driven model which serves as a virtual counterpart of physical equipment or systems.[lxii] It can be defined as *"an integrated simulation of a system that employs existing physics-based models, sensors, and fleet history to reproduce the behavior of its real counterpart."*[lxiii] A digital twin consists of three fundamental aspects that work in tandem to create a cohesive and dynamic model.[lxiv] First, there are the actual physical products, which are the tangible elements that exist in the real world. These products form the basis for replication in the digital domain. Second, there are the corresponding virtual representations, which are digital constructs mirroring the physical products in detail. These virtual models serve as the digital counterparts to the physical entities, replicating their attributes and behaviors. Finally, the third component comprises the data linkages. These are the channels that bridge the physical products with their virtual counterparts, facilitating a seamless flow of information. These linkages ensure that the virtual representations remain synchronized with their real-world counterparts, reflecting any changes or conditions in real time. Together, these components create a cohesive and dynamic system, enabling comprehensive analysis and optimization in various applications. Digital Twins are increasingly finding use cases within the energy sector.[lxv]

Digital twins play a pivotal role in forecasting energy demand and improving the management and distribution of the energy grid through real-time data-based simulation models. These virtual replicas are being leveraged for real-time module performance data, enabling rapid anomaly detection, maintenance scheduling and supporting service teams in maintaining system efficiency and reliability.[lxvi] [lxvii] [lxviii] This approach enhances system reliability, as seen in applications like California's Topaz Solar Farm for asset monitoring.[lxix] Additionally, digital twins simulate equipment behavior under various weather conditions, aiding wind farms in developing effective emergency response strategies to minimize damage and maintain a steady electricity supply.[lxx]

# Empowering consumers

In deregulated markets like the United States, where consumers have the freedom to choose their energy providers, AI plays a pivotal role in empowering them to make informed decisions.[lxxi] This is based on factors such as preferred energy sources, household budget, and consumption patterns.[lxxii] For instance, Carnegie Mellon University researchers have developed a machine learning system called Lumator. This system integrates the user's preferences and consumption data with various tariff plans, promotional rates, and product offers to recommend the most advantageous electricity supply deals.[lxxiii]

As the system learns more about the user's habits, it can automatically switch to more beneficial plans as they arise, ensuring a seamless energy supply. Such AI-driven solutions not only facilitate consumer choices but also promote the uptake of renewable energy by translating consumer preferences into tangible demand, thereby signaling to producers the consumer interest in renewable energy sources.[lxxiv]

# Discovery of new materials

AI-assisted methods are emerging as cost-effective and accelerated solutions in designing new materials for clean energy applications, addressing global needs for efficient and sustainable materials.

For instance, a typical electric vehicle (EV) battery, weighing approximately 500 kg, contains around 11.5 kg of lithium, 27 kg of nickel, 20 kg of manganese, 13.5 kg of cobalt, 91 kg of copper, and 180 kg of aluminum, steel, and plastic.[lxxv] The environmental impact of lithium extraction is striking, extracting one ton of lithium carbonate equivalent (LCE) from ore releases at least 15.8 tons of $CO_2$, while from brine, it's about 0.3 tons.[lxxvi] The water footprint is significant too, with brine extraction requiring around 470 tons of water per ton of lithium.[lxxvii]

Hence, progress in clean energy technologies would substantially benefit from discovering new materials that improve process efficiency, minimize carbon, water, and land footprints, and reduce both capital and operating costs. Here AI plays a substantive role. It is fascinating to take cognizance of developments such as the work of Google DeepMind researchers who have identified over 2.2 million crystal structures using an AI tool named GNoME in 2023.[lxxviii] The team intends to share 380,000 of the most promising structures with the scientific community for further experimentation and viability testing.[lxxix] The energy sector would potentially be one of the most prominent beneficiaries of this research, potentially leading to enhanced materials in the energy sector.

# Navigating the Complexities:

## AI's Challenges in Energy

In the evolving energy sector, the integration of AI presents a range of critical challenges. Central to these is the need for high-quality, accessible data, which is fundamental to the effective application of AI in this domain. This integration is further complicated by infrastructural constraints, especially evident when contemporary AI technologies face compatibility issues with existing legacy systems. Equally pertinent concern is the ethical application of AI, necessitating comprehensive strategies to protect sensitive data and maintain fairness. Additionally, the opaque nature of many AI applications, often described as 'black boxes', brings to the forefront issues of transparency, accountability, and potential bias.

## Data Quality

Data quality and availability is critical to the development and maintenance of effective energy infrastructure.[lxxx lxxxi] It directly impacts the reliability and sustainability of the energy sector, influencing a range of applications from early stage mapping and visualization to in depth technical and economic analysis.[lxxxii lxxxiii]

Incomplete, inaccurate, or inconsistent data can be the bane for modern energy infrastructure.[lxxxiv] Malfunctioning or poorly calibrated sensors lead to inaccurate data and misleading analysis.[lxxxv] Furthermore, sensors are often sensitive to environmental factors, including electromagnetic interference, radiofrequency interference, chemical exposure, and unexpected weather which could influence readings.[lxxxvi lxxxvii] Data collectors could experience time synchronization issues or calibration drifts that lead to gradual but virtually undetectable data diversions. Any data collection mishaps could lead to misleading or incomplete datasets which shouldn't be used in AI models regardless of data cleansing. This is especially concerning for AI in energy infrastructure because even minuscule data inaccuracies make a tremendous difference in energy infrastructure maintenance.

## Data Silos

The energy industry operates with multiple specialized systems that retain unique data formats and standards that may be incompatible with each other, making it harder for isolated raw data to be aggregated, standardized, and pre-processed for analysis[lxxxviii] Creating integrations between disparate data systems is feasible in certain scenarios, yet challenges such as geographic distribution, regulatory mandates, and the constraints of legacy systems often complicate this approach.

## Legacy Energy Infrastructure

Leveraging the benefits of AI in energy remains hindered by legacy energy infrastructure with lack of compatibility.[lxxxix xc xci] For instance, more than 70% of the electricity grid in the United States is over a quarter of a century old.[xcii] Obtaining a grid connection permit in Europe can require as much as eight years, indicating that a wind farm project initiated in 2023 might not become operational until after 2028.[xciii] These older systems were not designed with the modern capabilities of AI in mind, leading to issues of compatibility and integration. This mismatch can result in inefficiencies and limitations in harnessing AI's full potential in energy management and optimization.

## The Black Box Challenge

AI-based applications often function as mysterious 'black boxes' to consumers, who generally lack insight into their internal mechanisms and the processes behind their creation.[xciv]

This lack of transparency poses potential risks, including misuse due to misunderstanding, challenges in assigning accountability for faulty decisions, perpetuation of hidden biases, and privacy concerns. It also hinders the systems' improvement and trust-building among users and complicates regulatory compliance.

# Balancing Act: AI, Energy, and Optimal Regulation

The integration of AI in the energy sector presents a multifaceted challenge for policy makers, demanding the construction of policies that not only promote equitable and sustainable energy choices but also grapple with intricate issues such as data security, ethics of AI, and model transparency.

## Data Security

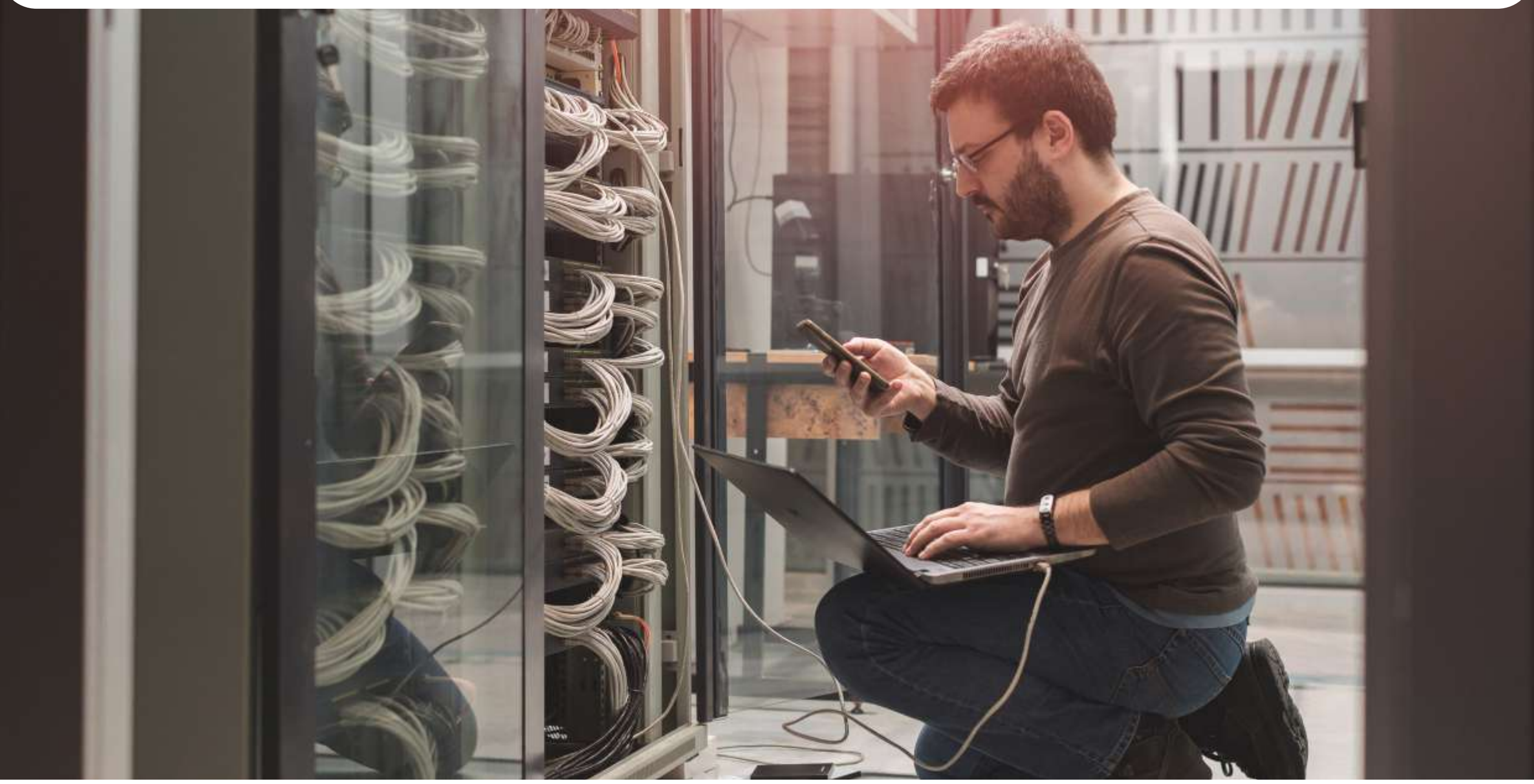
Energy infrastructure often requires sensitive data pertinent to economic and national security objectives. AI models would require a high volume of this sensitive data to train, suggest actionable insights, and trigger effective actions. Collecting usable data is necessary, but it needs to be complementary to high cybersecurity standards. Thus, the regulation of AI use necessitates a data privacy framework to provide standardized and effective protocols in the event of cyberattacks and unauthorized data breaches.[xcv]

## Ethical Use and Preventing Bias

AI models designed for predicting energy consumption and costs must adhere to strict ethical guidelines. This is particularly pertinent to ensure that these insights are not utilized for even inadvertently discriminatory pricing policies across different demographic groups. Furthermore, regulatory measures must be rigorously enforced for AI forecasting models which may have the potential to promote bias.[xcvi xcvii]

## AI Model Transparency

In the energy sector, AI model transparency involves openly revealing how data is utilized, detailing the specific types of data employed, and ensuring informed consent for its usage.[xcviii xcix] It also entails clear communication about the decision-making processes and algorithms within the model, ensuring that relevant stakeholders understand how AI conclusions are reached. Moreover, this transparency extends to openly addressing the model's limitations and uncertainties, fostering trust and informed decision-making among users, regulators, and the public.



# Trustworthy Perspective

As the energy sector increasingly embraces the myriad use cases of AI, it becomes imperative to navigate the challenges and intricacies that come with this frontier for building trust in this integration.

## Data Availability Enhancement

To enhance data availability for the application of AI in the energy sector, several strategies can be implemented.[c] Firstly, leveraging real-time data from electric power grids can provide a continuous stream of operational information.[ci] Additionally, utilizing data from residential smart utility meters can offer insights into consumer energy usage patterns.[cii] Building comprehensive databases that aggregate information on building energy consumption,[ciii] combined with satellite imagery,[civ] can provide a macro-level view of energy utilization across different regions. Moreover, tapping into social data such as cellular network data can reveal public behavior related to energy consumption.[cv]

Improving the spatial and temporal resolution of data collection methods can allow for a more detailed and nuanced understanding of how energy is used and produced, facilitating fine-grained analysis.[cvi] These facets would collectively increase the volume and variety of data available for AI algorithms in the energy sector, enabling more accurate modeling, prediction, and decision-making, and paving the way for more efficient and sustainable energy management.

## Data Quality, Privacy, and Security Framework

While data quality, privacy, and security are technically separate issues, strong data standardization frameworks must collectively account for each of these qualities not as separate issues, but rather as working parts of a whole. First, sensor technologies responsible for collecting data which would be used in AI models should be optimized to minimize operational failure. If such technology fails, there should be controls that human operators can quickly identify and mitigate the risks. Customer data used in operational optimization models, such as those forecasting energy consumption, should be encrypted and unidentifiable. Therefore, models must be required to employ highly secure encryption methods or employ "privacy-preserving" methods. Privacy-preserving machine learning refers to models that train and run based on data that cannot be directly identifiable. These privacy-preserving methods include federated learning,[cvii] multi-party computation (MPC),[cviii] zero-knowledge proofs,[cix] or a combination of these methods.

## Ethical Practices

As with most AI models, AI use in energy infrastructure must be designed to prevent discrimination and bias.[cx] [cxi] [cxii] Fostering a shared understanding of ethical practices will facilitate the widespread adoption of methods that enhance ethical evaluation and critical scrutiny of projects.[cxiii] It's imperative for international organizations to develop an ethical framework which can be adopted globally. Following this, companies should invest in programs such as training sessions that elevate awareness of ethical issues, thereby cultivating a community that is both ethics-aware and innovation-driven.[cxiv] This will aid in fostering a culture of AI in the energy sector that is firmly grounded in ethical principles.

## AI Model Transparency

Transparent AI models promote regulatory compliance, accountability, trust, and enables human oversight.[cxv] In the energy sector, there should be clearly defined transparency requirements, specifying aspects of an AI model which should be made available for establishing accountability. On the flip side, the framework should also require AI models to clearly disclose the parts of a model which will be protected for security or trade secret reasons. These transparent requirements would allow continuous monitoring, analysis, iteration of AI models to promote fair use cases.

## Phased Acceleration

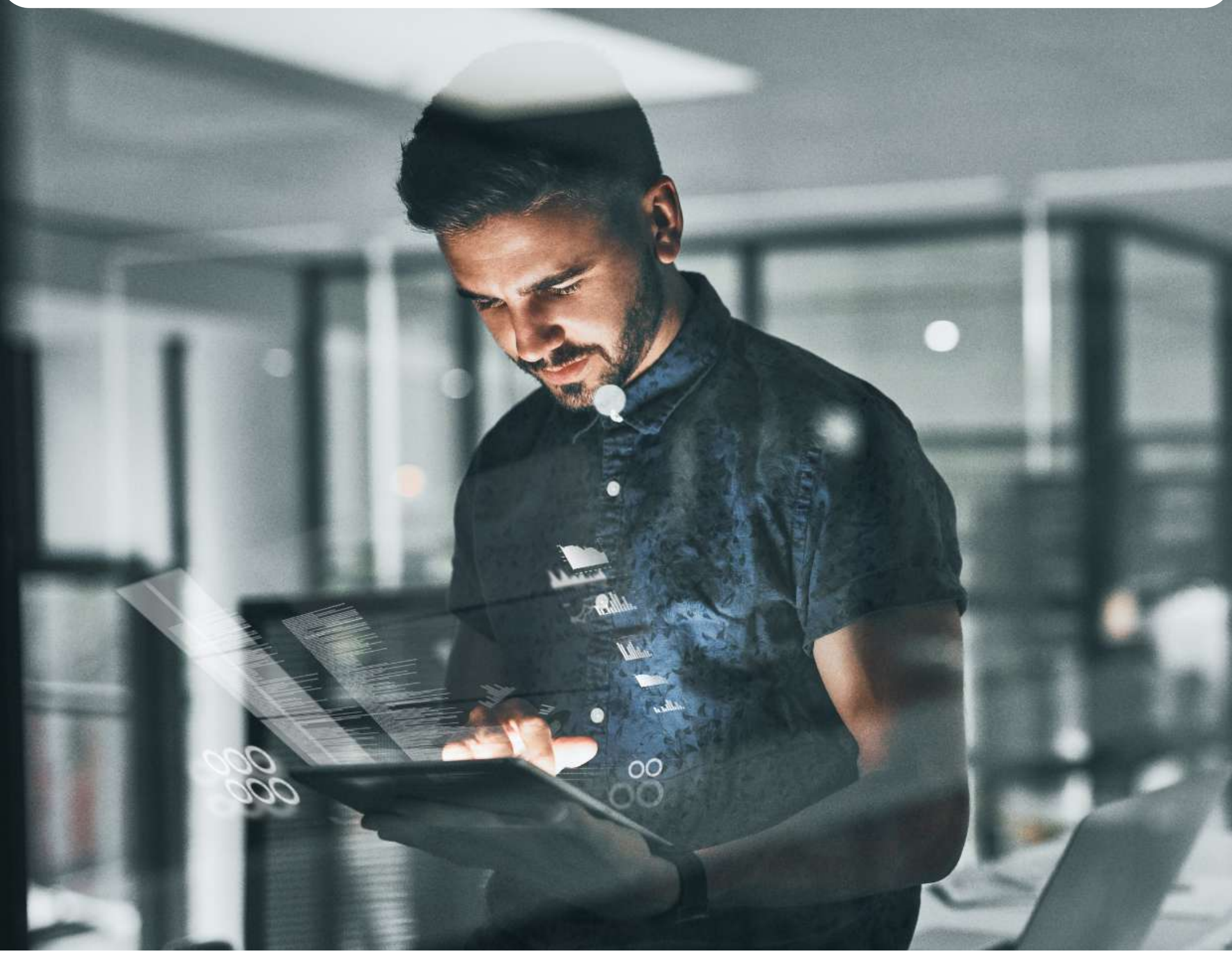
An accelerated yet phased approach to modernization of the existing energy infrastructure should be adopted. Starting with pilot projects or specific areas of the energy system allows for learning and adjustment before scaling up. Additionally, employing modular AI solutions that can be adapted to different parts of the energy system can reduce complexity.

## Fostering Synergy with Human-AI Collaboration

It is important to establishing mechanisms where AI-driven decisions are periodically reviewed and validated by human experts. This practice can ensure that AI actions are aligned with broader ethical goals and safety standards. Conducting regular training sessions for human operators, focusing on understanding the outputs of AI systems and the protocol for intervention is an important intervention which must be integrated within the energy workforce. Such education initiatives can significantly improve the collaborative dynamic between human operators and AI systems.

## Policies to Optimize AI Use in Energy

The AI energy sector would substantially benefit from a repository of progressive and future-facing regulations to optimize AI use in the industry. This could serve as a pivotal resource for policymakers globally, aiding in the promotion of advantageous AI applications across the globe while also being cognizant of preventing its various risks. While the actual execution of these regulatory frameworks would differ from country to country, it could play as essentially important role in being a resource that assists in the formulation, acknowledgment, and advocacy of effective regulations.



## Conclusion

The contemporary energy landscape is marked by an emphatic demand for solutions that are not only cost-effective and reliable but also environmentally sustainable and carbon neutral. In this context, AI has emerged as a pivotal force, transforming from a desirable tool to an indispensable asset in addressing global energy challenges with precision and innovative flair. The expanding role of AI in the energy sector extends far beyond mere technological advancements. It represents the advent of an era where innovation intersects with stewardship. This paradigm shift ensures that technological advancement is not just a progression in capability but also a stride towards crafting a more sustainable world for future generations. This underscores the importance of integrating AI in a manner that harmoniously balances technological progression with trust and responsibility. Emphasizing a deep commitment to responsible use and fostering a foundation of trust in AI applications is imperative for successfully leveraging AI's transformative potential in the energy sector.

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