BROOKINGS

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AI IN THE ELECTRICITY SECTOR

OPTIMIZING GRID MANAGEMENT AND ENERGY USE

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AUTHORS' NOTE

Aidan Kane led the work on this case study. These case studies were written as part of a joint project with David M. Byrne and Paul E. Soto of the Federal Reserve Board. We are indebted to them for assistance and helpful comments. We would also like to thank Eli Schrag for his factchecking.

Generative AI has undergone a surge in popularity recently, particularly with the introduction of Large Language Models (LLMs) like ChatGPT. There are numerous applications of AI throughout the economy, including many promising applications in the electricity sector. This sector's reliance on data and analytics, combined with the increasing complexity of the electricity grid from the introduction of new technologies, positions it to become a potential widespread adopter of generative AI. In this case study, we detail how generative AI is being used in the electricity sector by examining state-of-the-art research and use cases and then describe the interconnectedness of the electricity sector and the development of AI.

The case study is structured as follows: First, we provide an overview of the U.S. electricity sector and how it operates. Second, we discuss some of the applications of AI in the electricity sector and provide examples of how generative AI is being used to increase productivity of firms. Lastly, we examine the relationship between AI models and the electricity sector, focusing on the dynamics between AI's energy consumption and the increasing efficiency of the electricity sector from AI.

1. Overview of the US electricity sector

The U.S. electricity sector is a complex system composed of three main processes: electricity generation, transmission, and distribution (U.S. Environmental Protection Agency [EPA] 2022). Electricity is primarily generated through power plants and other utility-scale generators, which use a mix of renewable (e.g., hydro, wind, solar) and non-renewable energy (e.g., coal, natural gas) energy sources. After generation, electricity is then transferred via transmission and distribution lines to reach residential, commercial, and industrial users.

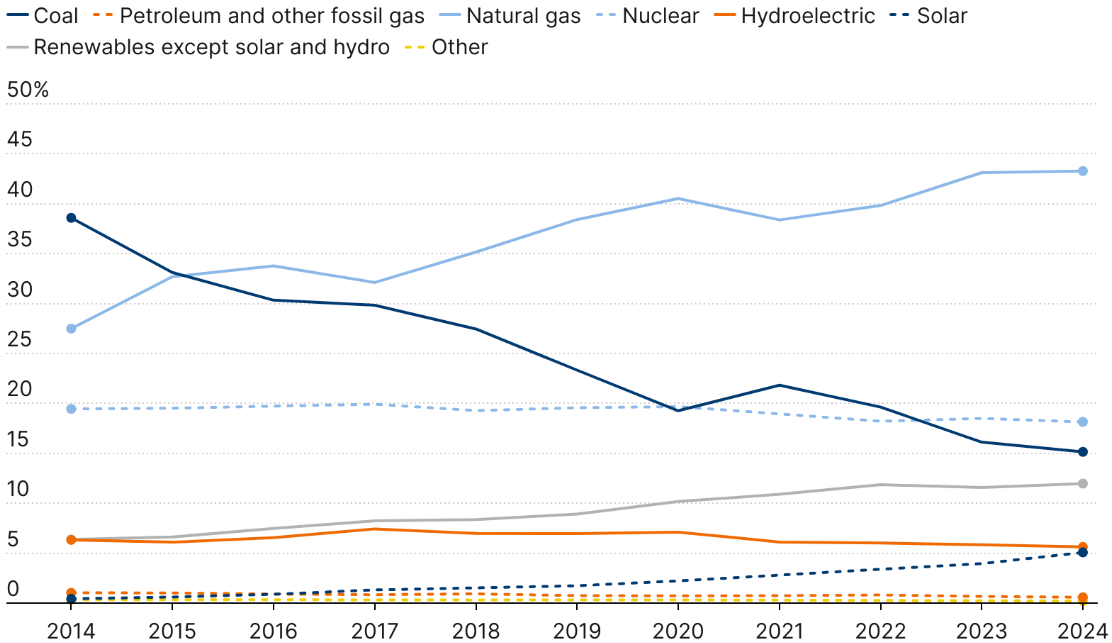
In recent years, the sector has undergone a shift towards decarbonization (Lawson 2018). Some of the main drivers of this include changing domestic policy and regulation and international agreements, both in response to climate change (Reuter et al. 2024). As climate change has increasingly affected the planet, there has been a greater focus on reducing the use of fossil fuels such as coal in the electricity sector. Also, regulations and policies such as the Inflation Reduction Act have shifted the sector towards addressing climate change by bolstering the use of renewable energy (Donohoo-Vallett 2023). In addition, international agreements to decarbonize such as the Paris Agreement motivate governments to shift towards decarbonization of the electricity sector ("How Are International Agreements Helping Fight Global Warming?" 2024). While the future of these agreements and policies in the U.S. is uncertain, the innovation and cost reductions in the sector will undoubtedly continue despite potential policy changes (The White House 2025; Fujii-Rajani and Patnaik 2025; Kane et al. 2025).

1.1. GENERATION

In order to generate electricity, fuels need to be converted into energy by electricity generators. Electricity production uses several different power sources, including coal, natural gas, petroleum, wind, solar, and hydropower. In 2024, Figure 1 shows that fossil fuels accounted for approximately 59% of total U.S. electricity generation, while renewables accounted for about 41%. In addition, the electricity generation sector has transitioned away from coal, which tends

FIGURE 1

Percentage of US total utility-scale electricity generation



Source: U.S. Energy Information Agency [EIA] (2025), Electric Power Monthly, Table 1.1.

Note: Data is a percentage of all generation, not including storage held into 2025.

to be more emissions-intensive than other sources, to utilize more natural gas, a less-emissions-intensive alternative to coal (U.S. Energy Information Agency [EIA] 2021).

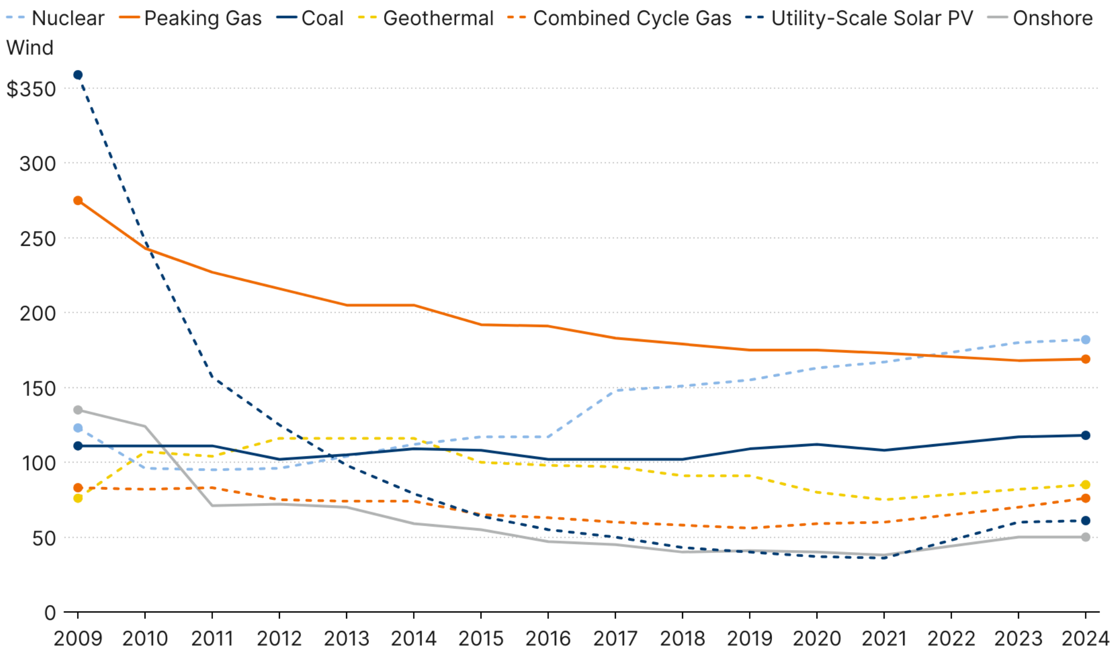
In the U.S., 42% of electricity is generated by steam turbines as of 2022, which burn fuels such as coal or natural gas to produce steam that then powers a generator's turbine (EIA 2023). There are also combustion gas electricity turbines that convert fuels into hot gases to turn blades in a turbine. Renewable energy turbines such as hydroelectric and wind turbines harness natural forces such as wind and water to spin turbine blades, creating electricity. Solar photovoltaic (PV) cells are turbine-less generators that convert the sun's energy into electricity.

The cost of renewable energy has decreased in recent years, making it more profitable to shift towards renewable energies. From 2010 to 2021, the costs of solar photovoltaics (PV) decreased by 88%, the costs of onshore wind decreased by 68%, and the cost of offshore wind decreased by 60% (Taylor et al. 2022). Forecasts show that renewable energy will continue to increase and take up more of total power production in the future ("Forecasting Share of Renewables in Final Consumption" n.d.).

In addition, fossil fuels are more expensive than utility-scale solar and onshore wind. As shown in Figure 2, the average cost per megawatt-hour ($/MWh) in 2024 was $61 for solar PV and $50 for onshore wind. These costs were lower than those of gas-powered plants—$169 for peaking plants and $76 for combined cycle—as well as coal-powered plants, which had a cost of $118 per megawatt-hour. Furthermore, according to the International Renewable Energy Agency, two-thirds of new renewable energy power installed in 2021 was cheaper than the cheapest coal-fired option in the G20 (Taylor et al. 2022).

FIGURE 2

Historical levelized cost of energy, unsubsidized average



Source: Lazard (2024)

Note: Data is in mean dollar per megawatt-hour ($/MWh).

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Different types of power plants have different types of efficiency rates, which measure the percentage of energy that is produced in a power plant that is converted into electricity. As seen in Figure 3, the efficiency rates of power plants have greatly increased over time. These efficiency gains have been achieved mainly by reducing heat loss in three main areas of a thermal power plant: the boiler (fuel heat is converted to steam), the turbine (steam is converted to mechanical rotational energy), and the generator (rotational energy is converted to electric power) (Cleveland et al. 2023). For renewables, wind power plants typically operate at around 35% to 47% efficiency while solar power plants operate at around 18% to 25% efficiency (Feng 2023; National Renewable Energy Laboratory n.d.). Hydroelectric power plants are highly efficient, operating at about 90% efficiency (Killingtveit 2020). This is because water is directly funneled to turbines that generate electricity, which results in little energy loss during the conversion process (Feng 2023).

1.2. TRANSMISSION AND DISTRIBUTION

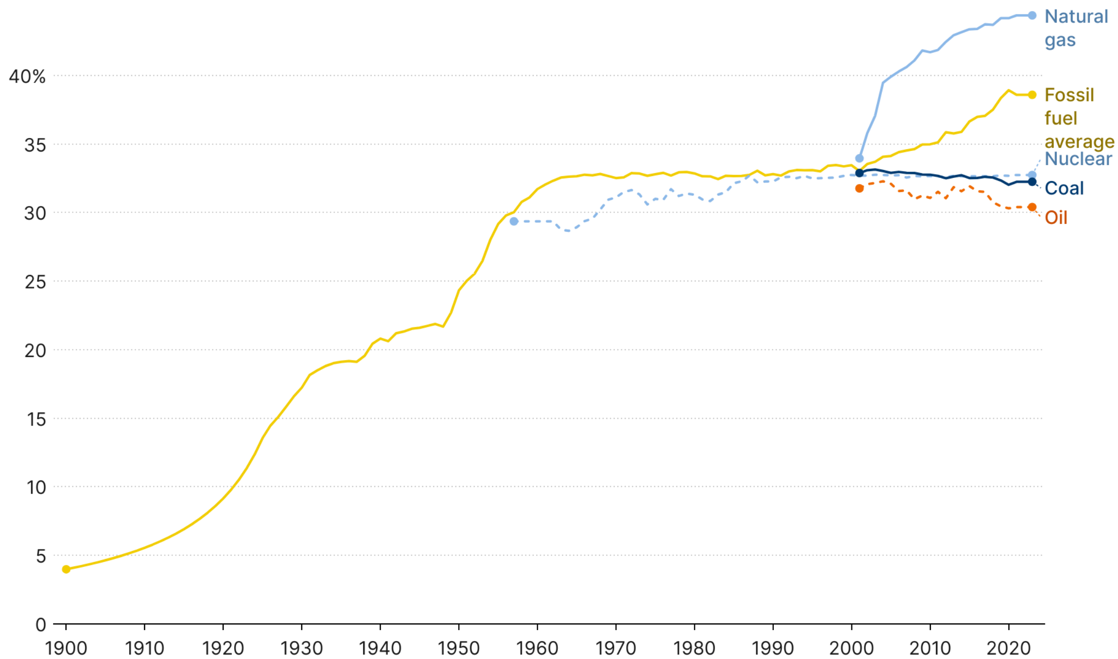
Once generated, electricity is stepped up to a higher voltage for efficient transmission across long-distance power lines that make up the transmission network (EIA 2024). The transmission system includes high-voltage lines, towers, substations, transformers, and monitoring systems.

The U.S. electrical grid, comprised of about 3,000 utilities and over 2 million miles of power lines, is divided into three major grid regions: Eastern, Western, and Texas (McBride and Siripurapu 2022). The grid regions, also known as interconnections, consist of distinct local electricity grids that together serve hundreds of millions of users. These grid interconnections link multiple local grids, enabling the transfer of electricity from areas with excess power to those experiencing a higher demand than their local production capacity (Garg 2022).

FIGURE 3

Thermal power plant efficiency in the United States

Efficiency is the heat content of a kilowatt-hour (kWh) of electricity divided by the heat rate of the power plant, which is the amount of energy used to generate on kWh of electricity.



Source: Cleveland et al. (2023)

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There are two types of renewable energy generation in the electricity sector: distributed and centralized, utility-scale generation. Distributed generation encompasses the small-scale renewable sources located on the distribution grid, typically at the residential or community level. Centralized, utility-scale generation refers to larger projects that connect to the grid through transmission lines (Cleary and Palmer 2020).

Historically, grids were developed to distribute electricity from a small number of producers to many users. Recent advances in the grid, such as the implementation of information technology and two-way flows of electricity, have led to the creation of the "smart grid." While not considered AI, the smart grid uses digital and advanced technologies to leverage two-way flows of electricity and information to establish an automated, distributed, and advanced energy delivery network (Fang et al. 2012). The smart grid is a modernized version of the 20th century power grid and improves coordination of the many components within a grid system, which lends itself well to the implementation of AI. A survey of the literature on smart grids found that innovations for the smart grid can be divided into three major systems: the smart infrastructure system, the smart protection system, and the smart management system (Fang et al. 2012). The smart infrastructure system includes communications, energy, and information supporting the smart grid, and facilitates the two-way flow of information and electricity. The smart management system provides key management and control services to the smart grid. The smart protection system protects against system failure and ensures the reliability, security, and privacy of the smart grid.

The rise of solar panels and other distributed generation technologies has further increased grid complexity. These technologies allow individuals and organizations to produce electricity themselves through consumer products such as solar panels. Traditionally, the grid was designed for one-way electricity flow from power plants to consumers. Now, the grid must support two-way transmission flows, allowing households and businesses to sell surplus electricity back to utility companies. This has been essential for integrating distributed energy resources into the modern grid.

The increasing integration of wind and solar energy presents challenges due to their variability. Fluctuations in renewable energy output make it difficult for grid operators to balance supply and demand of electricity, an integral aspect of ensuring the stability of the electricity grid. While statistical models help predict renewable energy availability, accurate forecasting remains a challenge.

2. Applications of AI in the electricity sector

The electricity sector is undergoing a significant transformation with the adoption of AI and other advanced technologies. As the industry faces increasing demands for efficiency, reliability, and sustainability, generative AI is emerging as a key tool for achieving these goals. Government agencies, international governmental organizations, and private companies are at the forefront of researching how AI can be integrated into the electricity sector, carefully considering its benefits and associated risks (Lakshmipathi 2023; Office of Cybersecurity, Energy Security, and Emergency Response 2024; Rozite et al. 2023).

One of the sector's strengths is its reliance on data analytics, which provides a foundation for adopting generative AI, a technology that thrives on large datasets. Power plants and transmission networks have collected extensive data from sensors and other monitoring systems, positioning the sector to take full advantage of generative AI's capabilities.

2.1. LOAD FORECASTING WITH GENERATIVE AI

Load forecasting is a key function of the electricity sector and ensures the efficiency, reliability, and economic feasibility of the grid. Accurate load forecasting ensures that resources are optimally allocated, lowers operating costs, and reduces the risk of grid instability (Liu et al. 2024). Traditional load forecasting methods, however, struggle to capture the complex, non-linear relationships in electricity consumption data, which can lead to inefficiencies and high operating costs.

Generative AI offers a potential solution by improving the accuracy and efficiency of load forecasting models (Avci 2023). By leveraging historical data, weather patterns, and socioeconomic factors, generative AI can predict electricity demand with greater precision, resulting in better resource management and planning (Jones 2023).

Recent advancements in AI, particularly the introduction of a data processing approach known as the "transformer architecture" (Vaswani et al. 2017), have shown significant potential in improving load forecasting. Where previous methods like Recurrent Neural Networks (RNNs) were limited by the requirement to process inputs sequentially, transformer-based models are able to process entire input sequences simultaneously, leading to shorter computational times (Chan and Yeo 2024). Chan and Yeo (2024) demonstrate the ability of transformers as electricity load forecasters, finding that their sparse transformer model attained similar accuracy to an RNN-based model while making predictions up to five times faster.

Large Language Models (LLMs) represent another promising development in time series and electricity load forecasting. Jin et al. (2024) developed a framework for repurposing LLMs for time series forecasting, finding that LLMs can outperform state-of-the-art forecasting methods across a wide range of applications. Furthermore, recent research shows that load forecasting can be significantly improved using LLMs. Gao et al. (2024) use a pre-trained language model in short-term load forecasting and find that their model outperforms other machine learning-based methods. Some studies suggest that LLM-based approaches may even surpass transformer-based techniques. Liu et al. (2024) apply an LLM to short-term load forecasting and report better performance compared to transformer-based forecasting.

Older generative models, such as Generative Adversarial Networks[1] (GANs) also have important use cases in electricity load forecasting. When data is limited for load forecasting, forecasting accuracy can suffer. Generative AI models can fill the gaps of limited data by generating synthetic data that can be used in time series forecasting. Aissa and Tarek (2024) developed a GAN-based model that generated a synthetic data set for electricity load data. This study found that using synthetic data improved the predictive accuracy of a forecasting model by 7.45%, largely due to a larger training database.

While the research on using generative AI for load forecasting is novel, some companies are beginning to use generative AI in their load forecasting processes. Gridmatic, a power marketer startup, uses generative AI in electricity load forecasting (Jones 2023). They developed a model of the U.S. grid that is used to forecast demand and renewable energy output. In addition, a pilot project by Gridmatic and EdgeConneX, an internet service provider, uses generative AI to enable 24/7, carbon-free energy for a Texas data center. This is done by forecasting and matching supply to demand on an hourly basis.

One case study found a major electricity distributor in eastern Turkey used a GAN model to improve their load forecasting processes (Avci 2023). The study found that this model outperformed the previously employed time series models and better captured the non-linear relationships in electricity consumption data.

2.2. PREDICTIVE MAINTENANCE AND VEGETATION MANAGEMENT

In addition to load forecasting, generative AI is making significant advancements in predictive maintenance and vegetation management, two areas that are vital for maintaining the reliability and safety of the electricity grid.

Predictive maintenance uses AI to identify which components of a power plant or grid are most likely to fail, enabling proactive repairs and reducing downtime (Office of Cybersecurity, Energy Security, and Emergency Response 2024). Generative AI can enhance this process by providing operators with detailed insights and recommendations. For instance, RetiPiù, an Italian gas and electric company, uses predictive and generative AI to conduct predictive maintenance (Engelhardt et al. 2024). The predictive AI model that RetiPiù is used to predict equipment malfunctions such as gas leaks. The generative AI system then automatically generates work orders, complete with maintenance schedules and status updates, streamlining the m−−−−−aintenance process and improving operational efficiency.

Vegetation management, particularly in transmission and distribution networks, is another area where generative AI is proving invaluable (Engelhardt et al. 2024). Managing vegetation near power lines is crucial for preventing outages and ensuring the safety of the grid, but it is also a costly and labor-intensive task. Generative AI can improve this process by analyzing satellite imagery and predicting tree growth patterns, helping utilities prioritize areas that require immediate attention.

A practical example of generative AI in this domain comes from an electricity distribution company in Turkey, which uses a Generative Adversarial Network (GAN) model to simulate potential equipment degradation under various conditions (Avci 2023). This approach has allowed the company to conduct preventative interventions, leading to a reduction in unexpected failures and an improvement in overall system reliability.

2.3. OTHER KEY APPLICATIONS OF GENERATIVE AI

Beyond load forecasting, predictive maintenance, and vegetation management, generative AI offers a wide range of applications that can enhance various aspects of the electricity sector.

Grid operators, for example, can benefit from fine-tuned generative AI models that support decisionmaking processes. The National Renewable Energy Laboratory conducted a study that introduced a fine-tuned generative AI model, eGridGPT, in the control room of grid operators (Choi et al. 2024). This model provides real-time analysis, suggestions, and decision recommendations, helping operators navigate complex scenarios and maintain grid stability.

Cybersecurity is another critical area where generative AI can make a significant impact. As the grid is increasingly digitized, it is more susceptible to cyberattacks. Therefore, the ability to detect and respond to such threats is more important than ever. Generative AI assists in cybersecurity by creating synthetic data that simulates cyberattack scenarios, enabling better preparation and response strategies. One paper uses a deep learning GAN algorithm to learn patterns in cyberattack messages and create additional cyberattack messages for detection (Ying et al. 2019). Having abundant data on cybersecurity attacks will help grid operators ensure that the grid sustains operation and avoids losses due to power outages caused by cyberattacks.

Generative AI is also being used to improve IT support within the electricity sector. Enel, a leading integrated electric utility company, worked with Amazon to automate their IT service desk tickets, boosting productivity for application management service teams by reducing time spent on repetitive service requests that are related to document procedures (Italiano 2024).

3. Energy consumption of AI

While AI holds immense potential for making energy systems more efficient through innovations such as smart grids and improvements to energy forecasting, its energy consumption poses significant challenges (SAP 2021). Training and operating sophisticated AI models, especially large-scale generative AI models built on deep learning, requires substantial computing power, which translates into high energy demands.

As of 2022, data centers, which are a crucial input for AI development and deployment, accounted for approximately 1-2% of total global electricity demand and around 3% of U.S. electricity demand (Davenport et al. 2024; Singer et al. 2024). Data center energy consumption is expected to grow to approximately 3-4% globally and 4.6-9.1% in the U.S. by 2030 (EPRI 2024; Singer et al. 2024). This growth is driven not only by the increasing prevalence of AI but also by the rise of other data-intensive and AI-related technologies such as the Internet of Things (IoT) and speech recognition.

3.1. BALANCING AI'S ENERGY CONSUMPTION WITH EFFICIENCY GAINS

Although AI remains reliant on heavy energy consumption, several innovations are enabling smaller AI models to perform at levels comparable to larger models, reducing the need for excessive energy consumption.

Some techniques contributing to this shift are model pruning, quantization, and knowledge distillation (EPRI 2024). Model pruning is a technique that reduces the number of unnecessary elements in neural networks, leading to robust performance while reducing computational requirements. Quantization is the practice of reducing the numerical accuracy of computations, resulting in lower computational costs without significant precision loss. Lastly, knowledge distillation is the process of creating smaller models with similar functionalities to larger models. These techniques all make AI systems more energy-efficient without sacrificing performance.

Other innovations in energy efficiency are also taking place in hardware. Specialized AI chips, such as tensor processing units (TPUs),[2] offer significant performance and energy efficiency improvements over other processing units (Khan 2020). In 2017, Google's first TPU provided 15x to 30x higher performance than GPUs and CPUs (Sato and Young 2017). Field-programmable gate arrays (FPGAs) and application-specific integrated circuits (ASICs) are two other specialized chips that are primarily used for inference, as they are more energy efficient than GPUs (Khan 2020). These energy-efficient hardware innovations are helping to mitigate the energy burden associated with AI training and inference.

3.2. CHALLENGES: JEVONS' PARADOX AND AI'S ENERGY FUTURE

However, while these advancements offer hope, there is a risk that energy efficiency gains may not necessarily lead to a decrease in overall energy consumption. This potential dilemma is reflected in Jevons' Paradox, which suggests that increases in efficiency can sometimes result in higher overall consumption, as lower costs encourage more widespread use (Alcott 2005). In the context of AI, as models become more efficient and accessible, demand for AI applications may surge, offsetting any energy savings.

For example, the increased deployment of AI across industries may drive up the number of AI models being trained and deployed globally. The growing use of generative AI applications and the widespread demand for real-time AI services will also likely increase the sector's energy footprint, even with improvements in model efficiency.

4. Conclusion

The complexity of the electricity sector in the U.S. lends itself well to the integration of generative AI. AI can augment humans in operating the electricity sector and the grid as the sector becomes increasingly complex with the introduction of new technologies.

As outlined in this report, there are many applications of generative AI in the electricity sector. From predictive maintenance to energy demand forecasting, the applications of AI in the electricity sector are broad and only going to continue to expand. As AI models improve, so will the applications of AI in the electricity sector, which could lend itself to improvements in productivity.

AI has the potential to enhance efficiency in the electricity sector, yet it also comes with a significant increase in energy consumption. While it remains unclear whether AI's efficiency gains will offset its increased energy consumption, it is evident that AI and the electricity sector are deeply interconnected. Historically, technological advancements and efficiency improvements have led to higher energy consumption, making it difficult to predict the net impact of AI on the sector.

Despite these uncertainties, AI is demonstrating productivity improvements in the electricity sector. By augmenting human labor, AI can help reduce errors, enhance efficiency, and lower operational costs. While this case study highlights current AI applications, continued advancements are likely to unlock even more innovation, shaping the future of productivity in the electricity sector.

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Endnotes

1 Generative adversarial networks are a type of generative AI model that are split into two parts: a generative model that generates data and a discriminative model that distinguishes between the real and synthetic data (Goodfellow et al. 2014). As the model is trained, the synthetic data created becomes so similar to the real data that, if training is done well, the discriminative model will be unable to distinguish between the real and fake data.

2 Tensor processing units are a type of ASIC that is specifically designed for matrix operations, the key computation used in training deep neural network AI models (Sato and Young 2017).