ARTIFICIAL INTELLIGENCE FOR CLIMATE CHANGE MITIGATION ROADMAP (SECOND EDITION)

CHAPTER 3:

POWER SYSTEM

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In 2023, carbon dioxide (CO_2) emissions from the global power sector were almost 15 Gt—roughly 28% of greenhouse gas (GHG) emissions globally.[1,2]

The power sector will play a central role in decarbonizing the global economy. Most strategies for deep decarbonization foresee growing reliance on the power sector as vehicles, industry, space heating and other sectors shift from fossil fuels to electricity. In the *Net Zero by 2050* scenario released by the International Energy Agency (IEA), for example, the share of electricity in final energy use increases from 20% in 2020 to 50% in 2050.[3] The amount of final energy use changes very little during this period, so the electric power sector more than doubles in size in the decades ahead in this scenario. Other scenarios are similar.[4]

For global climate change goals to be achieved, the power sector must grow and decarbonize at the same time. The scale of the challenge is enormous.

- Despite the extraordinary fall in the price of renewable power in the past 30 years, fossil fuels still dominate the global power sector. In 2023, fossil fuels (coal, oil and natural gas) generated 61% of the electricity produced globally. (In 1990, the figure was 65%.)[5]
- The impressive and record-breaking deployment of renewable power in the past decade has not been enough to meet the growth in the world's power demand in the same period.[6]
- Trillions of dollars are currently invested in legacy fossil fuel infrastructure globally. The average life of much of this infrastructure is several decades.[7-9]
- IEA analysis suggests that achieving net-zero emissions by mid-century will require global power sector investment to surge to roughly $3 trillion by 2030 (almost triple current levels) and stay at or near that level for decades.[3,10]

A challenge of this magnitude requires new technologies and approaches. The rapid advances in artificial intelligence (AI) have the potential to make a meaningful difference.[11,12] Indeed they are already starting to do so. For example:

- AI algorithms are predicting solar radiation and wind speeds more accurately than traditional methods, allowing for better scheduling and dispatch of renewable energy.

- Dynamic line rating and other AI-driven techniques have started to optimize transmission and distribution of electricity, ensuring that renewable energy is transmitted efficiently from generation sites to consumers.
- AI is facilitating demand response programs by analyzing consumption patterns and incentivizing consumers to shift their usage to periods of high renewable energy generation.
- AI is accelerating innovation in energy storage, evaluating new battery chemistries far more rapidly than traditional methods and accelerating deployment of vehicle-to-grid (V2G) and other distributed storage technologies.[13,14]

These steps are just a beginning. In the years ahead, AI could do much more to help reduce GHG emissions from the power sector, including in permitting reform, optimal power flow analyses, V2G charging and more.

At the same time, the rapid growth of AI creates challenges for decarbonizing the power sector. AI currently uses less than 1% of electricity generated globally, but power demand for AI is growing quickly. In many locations, demand for new data centers—driven in part by AI—is increasing faster than low-carbon power sources can be deployed. Power demand from new data centers is creating challenges for some utilities that are committed to decarbonizing their generation mix in the years ahead. This topic is discussed in more detail in Chapter 15 of this Roadmap.

This chapter explores how AI can contribute to decarbonizing the power sector. The chapter begins by exploring AI's current and potential impact in decarbonizing four parts of the power sector: (1) generation infrastructure, (2) transmission and distribution networks, (3) end-use sectors and (4) energy storage. The chapter then turns to barriers, risks, concluding thoughts and recommendations.

(This chapter mostly uses the term "AI" when referring to programs that perform tasks through inference of patterns and learning from data. In the technical literature, the term "machine learning" ("ML") is more common.)

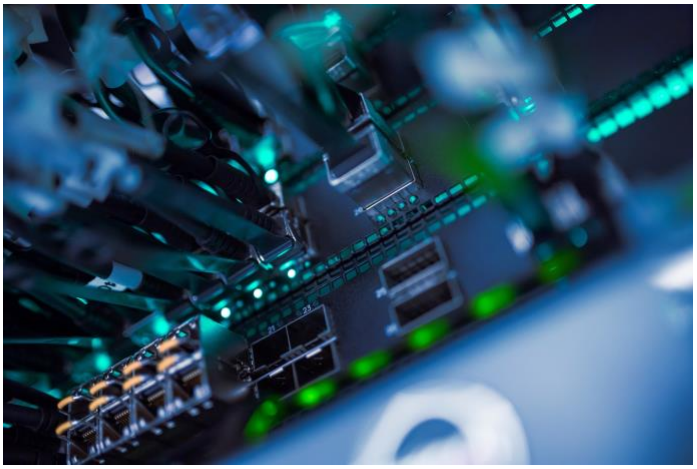
A. Generation

Planning and operating power generation infrastructure are complex tasks. Many factors require attention, including renewable resource availability, permitting constraints and the condition of physical assets. AI can help improve performance, speed deployment timelines and cut costs.

i. Planning

AI can be especially valuable in planning large-scale renewable projects:

- AI can recommend the optimal size and location of solar power projects, which requires complex calculations on topics such as weather patterns, equipment type and grid constraints.[15,16]
- AI can help with wind farm planning, which requires complex calculations on topics such as terrain, wind speed and direction, and turbine type.[17,18]
- AI can help accelerate deployment of non-conventional renewables, including wave energy[19] and geothermal energy.[20] In geothermal energy, AI can help improve numerical reservoir modeling, exploration, drilling and production.[19]



Permitting timelines are often a challenge for renewable projects. Large language models (LLMs) can extract text from past permit applications and decisions to help applicants improve application quality (see Benes et al., 2024[21] at p. 12–16). LLMs also help permitting authorities review permits more quickly and thoroughly (see e.g., Symbium[22]). At the US Department of Energy (DOE), several National Labs have initiated a pilot project using foundation models and other AI to systematically improve siting permitting and environmental reviews for renewables projects.[23]

AI can also help accelerate innovation in nuclear reactor design, speed the nuclear permitting process and cut costs in the operations of nuclear reactors.[24] (These topics are discussed in Chapter 10 of this Roadmap.)

ii. Operations

After renewable generation capacity is installed, operational decisions can have significant impacts on power output and costs. Predicting variable solar and wind power is one of the most well-studied topics in the use of AI in the power sector (see Figure 3-1).[25] For example:

- AI can predict weather relevant to wind/solar generation, such as cloud cover,[26] wind speed[27] and solar radiation[28]

- AI can integrate weather forecasts and power production forecasts (these forecasts typically focus on short-term predictions (<72 hours, mostly 24 hours) that rely on robust historical and real-time data)[29]
- Other applications for maximizing renewable power generation using AI include reinforcement learning control for wind turbines,[30,31] solar system operation[29] and solar shading[32]

Recent advances in AI-based weather forecasting are especially promising. In traditional weather forecasting, numerical models use sophisticated physics equations and historical weather data to predict atmospheric behavior. This is computationally expensive, requiring supercomputers for each prediction. In newer AI-based weather forecasting, ML techniques are used to train a model on historical weather data. Once the model is trained, the computational requirements to forecast atmospheric behavior are significantly less than with traditional methods.

Researchers around the world have made significant performance improvements using these new AI-based tools. In July 2023, scientists at Huawei Cloud released a paper in Nature[33] presenting AI-driven weather forecasting models that outperformed numerical methods. In November 2023, Google DeepMind released a paper[34] showing even more accurate results, especially for medium-range weather forecasts. Government agencies are starting to incorporate these new methods into their standard forecasts.[35]

As AI-based weather models become more accurate and less expensive, the use cases for these types of models will grow. In the power sector, AI-based weather models can increase output from solar and wind farms, help prepare for extreme weather events and contribute to system resilience. In North America, for example, AI is being used to help predict wildfires, synthesizing satellite images and LIDAR feeds in ways that can help grid operators make decisions on managing transmission lines through forests during periods of high wildfire risk.[36] (See Chapter 14 of this Roadmap, which explores how AI can help respond to extreme weather events.)

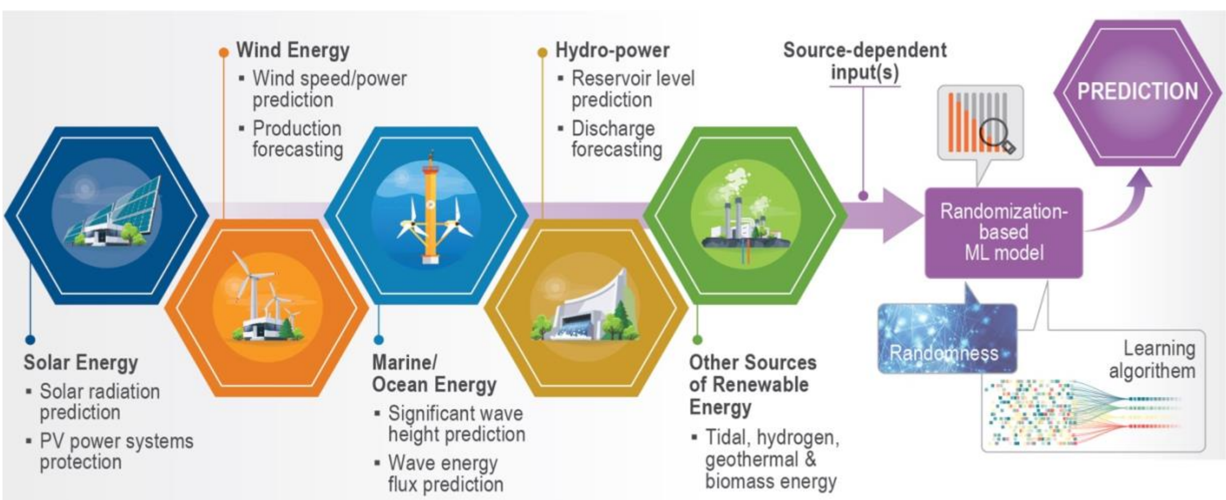


Figure 3-1. *AI predictions in renewable energy.*

AI can be especially helpful in operating rooftop solar photovoltaic (PV). AI can predict the power generation potential of rooftop solar panels,[37] generate forecasts[38] and reduce customer acquisition costs.[39]

Federated learning (FL)—a special type of AI—can be very useful in operating distributed power generation infrastructure. Federated learning is an AI technique where multiple decentralized devices collaboratively train a shared model while keeping the training data on the devices themselves, preserving data privacy and security.[40] FL is well-suited to tasks such as predicting rooftop solar generation[41] and can perform a number of tasks in the "smart city" and "smart grid" context.[42]

AI can also be used for preventive maintenance at power generation infrastructure. Data-driven predictions of maintenance and repair needs can minimize cost and production downtime. These predictions can be especially useful at wind power facilities, which are often located in difficult environments and must endure high wind speed, extreme temperatures and other challenges, making maintenance expensive.[43] AI can be used to schedule preventive maintenance, reducing turbine failure and repair costs.[43,44] AI can also be used to improve maintenance at solar,[45] nuclear[46] and hydro[47] power plants.

Finally, AI can assist with integrating the electric grid and emerging low-carbon hydrogen networks. Green hydrogen production will consume enormous power. Optimizing integration of the electric grid with green hydrogen production can deliver significant savings.[48] AI can help optimize green hydrogen production by predicting renewable power potential,[49] curtailed renewable energy[50] and water sustainability.[51] AI can also help plan hydrogen refueling stations, optimizing station-based production and storage.[52] AI can be used to integrate renewable power with hydrogen-energy storage to increase grid stability and lower peak loads.[53]

B. Transmission and Distribution

Investing in transmission and distribution infrastructure is essential for integrating high volumes of renewable power into the electric grid. Renewable resources are often located far away from load centers, requiring long-distance transmission. Planning and operating this infrastructure involves solving complicated nonlinear problems. AI tools can help with many aspects of electricity transmission and distribution—cutting costs, increasing capacity and helping reduce GHG emissions.[54]

AI can be especially helpful with transmission expansion planning (TEP). Determining the best location and capacity of new transmission lines involves large-scale complex optimization problems in which finding a feasible solution can be difficult.[55] These difficulties, along with a large increase in the number of interconnection requests, are causing significant delays and uncertainties in permitting renewable power projects in the United States and other geographies.

Several studies highlight the potential for AI to contribute to TEP:

- Borozan et al. (2023) integrated AI with well-established TEP decomposition methods to improve computational efficiency while preserving solution quality[56]
- Wang et al. (2021a and b) showed that AI can be used to solve multi-stage TEP based on a static model, which can be flexibly adjusted and incorporate uncertainties in wind power and demand projections[57,58]
- Fu et al. (2020) studied the stochastic optimal planning of distribution networks using AI, considering both renewable power and demand variability[59]

AI can be especially helpful in optimal power flow (OPF) analysis—an integral part of TEP that evaluates the most efficient and reliable flow of electricity through a transmission network while meeting operational constraints and minimizing costs. AI can significantly improve the process of solving alternating current optimal power flow (AC-OPF) problems by evaluating transmission expansion results much more efficiently than current methods.[60,61] This improvement not only increases accuracy over traditional direct current optimal power flow (DC-OPF) systems but also has the potential to make transmission permitting faster. Leveraging AI for AC-OPF can lead to better transmission expansion planning, helping reduce emissions from the power system.[62,63]

Another promising application of AI is for dynamic line rating -- a method of determining the maximum capacity of transmission lines based on current weather and line conditions instead of static, conservative estimates.[64] Dynamic line rating can increase the capacity of transmission lines by at least 30%.[65,66] Increasing the capacity of existing transmission lines is especially valuable where permitting new transmission lines to bring renewable power to load centers is difficult. AI-driven dynamic line rating can help maximize utilization of renewable resources and support integration of more renewable power into the electric grid.[67]

AI can also help distribution network operations. Historically, the distribution grid was too complex to be mapped accurately, leading to difficulties with fault detection. Recent progress in digitalization has increased the observability and controllability of the distribution grid, enabling AI to assist in fault detection.[68] Studies have shown that AI methods outperform traditional methods in fault detection accuracy but demand large amounts of data and significant computational resources.[68,69] Better fault detection can reduce GHG emissions by minimizing downtime, reducing the need for carbon-intensive backup power and ensuring grid stability, which supports integration of renewable power.[70,71]

In conclusion, AI is being used in transmission and distribution infrastructure to improve expansion planning, renewables integration and core operations. As costs decline and AI capabilities continue to improve, AI can play an increasingly important role in transmission and distribution.[72]

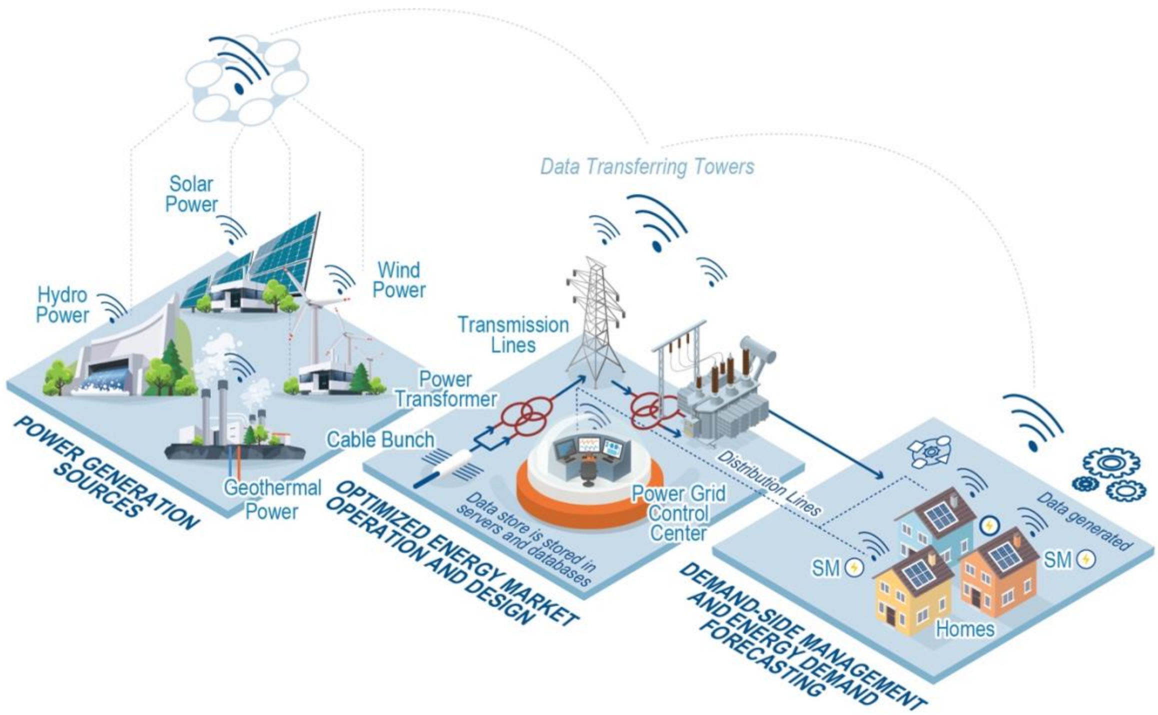


Figure 3-2. Power grid with data transfer

C. End-Use Devices

"End-use devices" include appliances, lighting, electric vehicles (EVs), air conditioning and any other equipment that consumes electricity. In 2023, there were roughly 13 billion end-use devices with automated sensors and controls globally.[73] Better management of these end-use devices can help significantly improve energy efficiency and reduce GHG emissions.

AI can play a central role in managing end-use devices. Indeed, AI tools are essential for leveraging the enormous quantities of data from end-use devices into performance gains. AI can predict energy demand patterns and adjust device settings to improve efficiency, cut energy use and reduce emissions. AI can optimize operation of smart devices, such as appliances, lighting systems and thermostats, to ensure these devices consume less energy during periods of high demand or low renewable power supplies. AI can facilitate demand response programs, virtual power plants, EV charging and peer-to-peer energy trading.

Demand prediction using AI already exhibits great potential. AI can predict general energy demand patterns[74] and demand patterns for specific sectors, such as buildings[75] and EV charging.[76] These demand predictions can be used for system operations, including for unit commitment (short-term) and system planning (long-term).

Aside from passively predicting electricity demand, AI can also be used to actively reshape demand profiles. In demand response programs, volunteers agree to limit electricity consumption for financial reward. This helps reduce GHG emissions by avoiding the need to turn on peaker plants for additional electricity generation. Antonopoulos et al. (2020) reviewed AI approaches for demand response, finding that AI can capture human feedback and motivate electricity users to participate in demand response programs.[77] Demand-side AI tools require significant data with high spatiotemporal resolution, which requires enabling infrastructure (such as smart meters) and can create privacy concerns.

AI plays an especially important role in virtual power plants (VPPs) -- networks of decentralized, distributed energy resources including end-use devices that are integrated and managed using advanced software.[78,79] VPPs reduce GHG emissions by helping integrate renewable power into electric grids and (like demand response programs) helping limit the need for peaker plants. Many VPPs combine AI-driven demand predictions and the ability to manipulate the power demand of end-use devices:

- Several US states facing peak demand problems have programs to combine consumer assets, including home batteries, smart thermostats, EVs and more, into a VPP. By controlling these devices in aggregate and making small changes to their operational programming, utilities and retailers can shift load from times of peak demand and peak prices, reducing overall costs.[80]
- In Japan, the Kyocera Corporation has implemented an AI-driven VPP system that aggregates energy from numerous distributed sources, including solar panels and battery storage, to optimize energy distribution and balance supply and demand in real time.[81]
- In Germany, Next Kraftwerke operates a VPP that uses AI to manage over 10,000 decentralized energy units.[82]
- One report suggests the savings from VPPs in California could help utilities save up to $755 million in power system costs, while consumers could save up to $550 million per year by 2035 if the current trajectory of VPP deployment continues.[83]

AI can be especially helpful with EV charging. AI tools can help optimize EV charging station locations, predict EV power demand, increase EV charger utilization, schedule EV charging to reduce costs and implement V2G programs.[84-86] (See discussion of V2G programs below.)

Finally, AI can help establish intelligent peer-to-peer energy trading platforms and predictive analysis.[87,88] Peer-to-peer energy can help reduce GHG emissions in several ways, such as by allowing households and businesses with solar PV panels to sell excess clean energy directly to other consumers and by reducing the distance electricity needs to travel, cutting transmission and distribution losses.[89,90]

In conclusion, AI could play an important role in managing end-use devices—helping to optimize their operation, increase energy efficiency and reduce GHG emissions.

D. Energy Storage

As more solar and wind power is deployed, energy storage is becoming an essential part of the electric grid. Energy storage balances temporal mismatch in supply and demand, serving as both generation and load. AI can help plan for energy storage, schedule its operation and optimize its lifetime value. AI can also help accelerate innovation in energy storage.

Energy storage is growing significantly around the world. In the United States, the investment tax credit for stand-alone storage in the Inflation Reduction Act of 2022 creates powerful new incentives for utility scale battery storage, and deployment is growing rapidly.[91,92] In China, battery storage featured prominently in the 14th Five Year Plan (2021–2025), which directed more than 100 billion RMB to the market. In 2023, newly installed capacity was nearly 50 GWh, an increase of more than 60% from the end of 2022.[93] In Europe, battery storage installations are led by the United Kingdom, Germany and Italy, where policy incentives and high energy prices are creating ideal market conditions for rapid deployment, especially alongside renewable power generation.[94,95]

Types of energy storage systems include (1) electrochemical storage, such as lithium-ion batteries, flow batteries and capacitors; 2) pumped hydro energy; 3) chemical storage, such as hydrogen; 4) thermal storage, such as molten salt, paraffin and metals and 5) mechanical storage, such as flywheels and compressed air.[96]

AI can help integrate energy storage into power grids, predicting when renewable power will be curtailed and supporting energy storage scheduling more broadly.[50,97,98] AI can also help battery owners plan for maintenance and replacement of energy storage assets.[99,100]

AI is especially well-suited to energy storage due to the dynamic nature of the optimization needed for battery management. Battery storage operators must consider many factors in making decisions, including safety, market signals and weather at the site of related solar and wind power facilities. Multi-factor models with this level of complexity are well-suited to AI algorithms for finding optimal variables on very short timeframes. Many AI algorithms are fast to train and deploy and can be very effective in helping operators respond to real-time market conditions to maximize revenue and optimize asset usage.

AI has a range of other benefits for energy storage, including preventive maintenance and optimization of consumable components, such as rolling bearings of flywheel-battery hybrid storage.[101] AI can be used to optimize combined systems, such as those with wind, pumped hydro and hydrogen[102]; integrate price and energy forecasts for hydrogen energy storage operation and control[103]; and (as discussed in Chapter 13) accelerate innovation in battery chemistry.

EVs have significant potential as distributed energy storage, sometimes referred to as mobile energy storage, V2G or vehicle-to-everything (V2X).[104] Aggregated volumes of energy storage in EV are very large in scale—many times greater than deployed amounts of stationary storage. Most vehicles are parked most of the time. However, to use EVs as grid assets, grid managers must understand and pay careful attention to drivers' use of their vehicles for mobility services, which will be a priority for most drivers in most situations. AI can be used for predicting user charging behaviors,[105] helping solve vehicle routing optimization problems[106] and improving V2G performance.[107,108] AI can maximize the value of data collected from vehicles, facilitating deployment of V2G technologies.

E. Barriers

Several barriers limit the adoption of AI for decarbonization of the power sector.

First, the use of AI in the power sector is limited by poor data quality and governance. The accuracy and efficacy of any AI modeling technique depends on clean, well-organized and well-governed data. Many parts of the power sector will need to invest in making their data available in an industry-standard way. The myriad benefits of AI discussed above will be limited unless the underlying inputs can be cleaned, organized and deployed in a way that AI models can consume.

In the United States, for example, standardized data (in tables with descriptions and access points that are the same across each organization) do not exist in the power sector today. Utilities, independent system operators (ISOs) and regional transmission organizations (RTOs) make data available in slightly different ways—across different time horizons, in different formats and with different frequencies—thus making it impossible to do analysis across all the relevant players in the power system. Private companies and the US Energy Information Administration (EIA) are doing some of this standardization work, but getting comparable data sets across all major US regions at a granular level remains very onerous from a data engineering perspective. Thoughtful governance to reduce privacy risks and model bias stemming from poor quality data is also essential.

Second, the lack of AI-training in the workforce is a significant barrier. AI's application in grid infrastructure requires a workforce that is knowledgeable on both the electric grid and AI. This knowledge base is important for research and development (R&D), technology deployment and policy design. The rapid advance of AI in software and technology systems will yield the best results if workers are equipped with a baseline of strong technical skills to understand the appropriate and safe use cases for AI.

Finally, poor market design can hinder adoption of AI in the power sector. When market structures do not adequately reward innovation or the integration of advanced technologies like AI, utilities and other stakeholders may be reluctant to invest in AI-driven solutions. Fragmented markets and inconsistent regulations across regions can complicate the deployment of AI, limiting its potential to optimize energy systems, reduce emissions and enhance grid reliability.

F. Risks

Deploying AI in the power sector creates a number of serious risks, including those related to bias, invasions of privacy, safety and security.

First, AI can lead to biased outcomes when training data do not accurately represent real-world conditions. For example, an AI model trained on power system data without adequate information on poor communities could recommend infrastructure investments that fail to adequately serve those communities. A model trained on data from the Global North could produce inaccurate information or suboptimal outcomes when used in the Global South. Data sets from one region could work poorly in another region due to differences in weather conditions, topographies or other factors.

Second, use of AI in the power sector could result in privacy breaches. AI systems require large amounts of data to function well. Data collection on topics such as energy consumption patterns and customer payment histories may be important for some AI applications but creates a risk of unauthorized access, identity theft and related problems. (This risk principally occurs with respect to AI in end-use devices and with distribution utilities—not with use of AI in generation, transmission or energy storage.)

Third, catastrophic failures could result if an AI system recommends or makes an incorrect decision due to a flaw in its algorithm or an unforeseen situation. Such failures could include equipment damage, power outages or worse. Rigorous testing, continuous monitoring and robust fail-safe mechanisms are crucial to ensure the safety of AI-operated energy systems. Transparency and interpretability of AI models are essential to create trust in AI systems.

Fourth, AI systems are susceptible to cyberattacks, including adversarial attacks where malicious actors manipulate the AI's input data to cause harmful outputs. Such attacks can compromise the integrity of the AI system, leading to incorrect decisions that could disrupt power supply, damage infrastructure or even facilitate further attacks on the grid. Robust cybersecurity measures, regular updates and stringent access controls are essential to protect AI systems from such threats.

In April 2024, the US DOE released a report on *Potential Benefits and Risks of Artificial Intelligence for Critical Energy Infrastructure,* which found that:

> *"while a number of significant risks exist if AI is used or deployed naïvely, most risks can be mitigated through best practices, putting appropriate protections around important data and models, and in some cases, funding further research on mitigation techniques."*[109]

G. Conclusion

In summary, AI has significant potential to help decarbonize the power sector in several areas.

- Short-term predictions based on time-series data. Predictions of electricity demand, solar availability and wind speed are necessary for operating electric grids and power markets. These types of data follow certain physical laws and patterns of human behavior but are intrinsically stochastic. Prediction is possible but difficult with conventional non-AI algorithms. AI can detect patterns in historical data that improve predictive abilities enormously.

- Scenario development, such as for EV charging and renewable power deployment. These scenarios are important to guide grid planning, especially in light of uncertainties related to climate change impacts and the deployment of new technologies. If rich historical data are available, AI tools can help significantly with these tasks.
- Improving optimization, such as for planning problems. Many power grid optimization problems involve work with large, nonlinear models. AI can speed computation, improve feature extraction and help solve "optimization unsolvable" problems, such as stochastic planning. Data support for these model-based problems is generally less critical than in other areas.
- System integration and operation. The grid infrastructure is becoming more and more inclusive and increasingly exposed to real-time uncertainties, such as wind/solar fluctuation. Taking a systematic view, instead of focusing on certain grid components, is more critical than in the past. Furthermore, grid operations have objectives related to cost, reliability, resilience, equity GHG emissions. AI shows great promise in helping grid managers understand more complex and quickly evolving grid infrastructure.

AI has potential application in nearly all aspects of power-sector management, including planning, monitoring, maintenance and operations. AI is becoming an important tool to help decarbonize the power sector. However, AI tools for decarbonization are not yet widely deployed. Barriers must be overcome and several risks must be addressed to realize AI's full potential to contribute to power sector decarbonization.

H. Recommendations

1. *Utilities and independent power producers should use AI tools for a wide range of purposes, including helping to plan renewables projects, monitor the condition of power equipment, integrate distributed energy resources into the grid, run demand response programs and optimize the use of energy storage systems. In doing so, utilities and independent power producers should prioritize rigorous testing, continuous monitoring and robust fail-safe mechanisms, setting benchmarks for the transparency of AI systems.*

2. *Electricity regulators should create clear regulatory frameworks to support using AI in energy management. These frameworks should include rates that provide cost recovery for AI-related investments, such as smart meters, sensors and open-source grid management software. The frameworks should address risks related to data privacy, safety and cybersecurity.*

3. *National governments, electricity regulators and utilities should work together to develop and enforce data standards for all aspects of grid operations. Regional governing bodies, such as the US ISOs and RTOs, should prioritize standardization of data to enable cross-regional analysis. These data should be available in industry standard formats in free and publicly available portals for use in AI modeling and research.*

4. *Utilities, regulatory agencies and academic experts should work together to develop AI-driven AC-OPF (alternating current-optimal power flow) models and permitting reforms. These models should be used to reduce delays in the interconnection process and accelerate deployment of new renewable generation sources to the grid.*

5. *Academic experts should emphasize geographic specificity in AI-driven weather models to increase the utility of weather forecasting for renewable energy production within specific boundaries (e.g., ISOs, climate zones). These experts should develop models that forecast within a smaller range than nearby weather station radii, focusing on wind direction, wind speed, solar radiation and cloud cover.*

6. *Utilities and electricity regulators should launch programs for training workers in the power sector to assess and use AI-driven technologies.*

7. *National governments should encourage and fund collaborative R&D projects between academic institutions, industry and utilities focused on AI and related applications for renewable power, energy efficiency and emissions reduction, including AI-driven forecasting tools and grid management systems.*

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