U.S. DEPARTMENT OF ENERGY

AI for Energy

Opportunities for a Modern Grid and Clean Energy Economy

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List of Acronyms

ABPDU	Advanced Biofuels and Bioproducts Process Development Unit
ADMS	Advanced Distribution Management System
AI	Artificial Intelligence
AMBER	Artificial Intelligence and Machine Learning for Bioenergy Research
AMMTO	DOE Advanced Materials and Manufacturing Technology Office
ARPA-E	Advanced Research Projects Agency - Energy
BER	Biological and Environmental Research Program
BETO	DOE Bioenergy Technologies Office
BIL	Bipartisan Infrastructure Law
BTO	DOE Building Technologies Office
CCS	Carbon Capture and Storage
CEQ	White House Council on Environmental Quality
CESER	DOE Office of Cybersecurity, Energy Security, and Emergency Response
CESMII	Clean Energy Smart Manufacturing Innovation Institute
CMM	Critical Minerals and Materials
CMRA	Climate Mapping for Resilience and Adaptation
CPUC	California Public Utility Commission
DBMS	Database Management System
DCEP	Data Center Energy Practitioner
DER	Distributed Energy Resource
DLR	Dynamic Line Rating
DOE	Department of Energy
ECOS	Environmental Conservation Online System
EIS	Environmental Impact Statement
EMS	Emergency Management System
EO	Executive Order
EPA	Environmental Protection Agency
ESA	Endangered Species Act
EV	Electric Vehicle
EVSE	Electric Vehicle Supply Equipment
FECM	DOE Office of Fossil Energy and Carbon Management
FERC	Federal Energy Regulatory Commission
FOA	Funding Opportunity Announcement
GDO	DOE Grid Deployment Office
GEB	Grid-Interactive Efficient Buildings
GET	Grid-Enhancing Technologies
GHG	Greenhouse Gas
GIS	Geographic Information System
GW	Gigawatt
HITL	Human-in-the-Loop

HVAC	Heating, Ventilation, and Air Conditioning
IoT	Internet of Things
IRA	Inflation Reduction Act
JGI	Joint Genome Institute
LBNL	Lawrence Berkeley National Laboratory
LLM	Large Language Model
LMM	Large Multimodal Model
ML	Machine Learning
NE	DOE Office of Nuclear Energy
NEPA	National Environmental Policy Act
NERC	North American Electric Reliability Corporation
NETL	National Energy Technology Laboratory
NGO	Non-Governmental Organization
NHPA	National Historic Preservation Act
NLP	Natural Language Processing
NREL	National Renewable Energy Laboratory
NSF	U.S. National Science Foundation
O&M	Operations and Maintenance
OE	DOE Office of Electricity
OEM	Original Equipment Manufacturer
ORNL	Oak Ridge National Laboratory
OSTP	White House Office of Science and Technology Policy
PET	Privacy Enhancing Technology
PMU	Phasor Measurement Units
PPA	Power Purchase Agreement
PUE	Power Usage Effectiveness
PV	Photovoltaic
R&D	Research & Development
RAG	Retrieval-Augmented Generation
RCN	Research Coordination Network
RFI	Request for Information
RUL	Remaining Useful Life
SCADA	Supervisory Control and Data Acquisition
T&D	Transmission and Distribution
TO	Topology Optimization
TPU	Tensor Processing Unit
USDA	U.S. Department of Agriculture
V2V	Vehicle-to-Vehicle
VGI	Vehicle-Grid Integration
VPP	Virtual Power Plant

Executive Summary

This report was prepared pursuant to the Executive Order (E.O.) on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence (AI) (14110), issued October 30, 2023. Priority use cases have been identified in four broad areas where AI can be immediately deployed to improve the grid while achieving the Administration's goals for reducing emissions and providing affordable and reliable electricity to all Americans: grid planning, permitting and siting, operations and reliability, and resilience. The report also addresses opportunities for AI to address the clean energy economy more broadly and the associated challenges.

To ensure the Safe, Secure, and Trustworthy Development and Use of AI, President Biden signed E.O. 14110 on October 30, 2023. Section 5.2(g) of the E.O. calls for the issuance of a public report "describing the potential for AI to improve planning, permitting, investment, and operations for electric grid infrastructure and to enable the provision of clean, affordable, reliable, resilient, and secure electric power to all Americans." This report summarizes these opportunities as well as how to maintain safety, security, and reliability for AI applications on the grid.

Achieving President Biden's goal of building an equitable clean energy economy by 2050 while strengthening the Nation's resilience against climate change will require a substantial increase in the rate of modernization and decarbonization of the electrical grid of the United States. Emerging applications for AI offer the potential to enable change on the grid at a non-linear pace and scale, while unlocking opportunities to accelerate the broader transition to a clean energy economy in sectors like transportation, industry, and buildings – with the right cross-sector coordination and commitment in place.

The electrical grid of the United States is among the most complex machines on earth. It consists of tens of thousands of power generators delivering electricity across more than 600,000 circuit miles of transmission lines, 70,000 substations, 5.5 million miles of distribution lines, and 180 million power poles.[1] This system evolved organically over a century of piecemeal additions, and now operates at the heart of America's $28 trillion economy (GDP, Q4 2023).[2] While the grid is generally highly reliable today, this infrastructure is becoming old and overburdened, and outages already cost American businesses $150 billion annually.[3] Several coinciding trends – including electrification, renewable power growth, growing demand, and the rising threat of wildfires and other climate-change-related weather events – are now putting new pressures on a grid that was built on unidirectional energy flows and with very little performance information from sensors.

Modernizing and decarbonizing the grid of the United States are critical paths to meeting the President's energy goals. A modern grid is one that allows grid managers to make decisions based on multi-directional flows of energy and information, rapidly integrate new carbon free generation sources like wind and solar, actively balance both electricity supply and demand (including increasing electrification and integration of grid-connected distributed energy resources), and proactively mitigate risks associated with climate change and extreme events.

Realizing these shifts requires optimizing four key areas of grid management: planning, permitting, operations and reliability, and resilience. AI has the potential to significantly improve all these areas of grid management. Some key highlights include AI-accelerated power grid models for capacity and transmission studies, large language models to assist compliance and review with Federal permitting, advanced AI to forecast renewable energy production for grid operators, and smart grid applications of AI to enhance resilience.

It is crucial that these new AI use cases do not introduce new risks to the grid. The power grid must deliver power reliably every hour of every day, even as rapid transformations are occurring. To ensure safety, security, and reliability, AI models for grid applications should be rigorously validated, interpretable, ethically implemented with humans-in-the-loop, scalable in performance, physically informed (where relevant), and adhere to power grid governance standards.

Beyond just the grid, AI could support a range of applications to help advance an equitable clean energy economy. Reaching net-zero greenhouse gas (GHG) emissions across the economy requires addressing unique challenges across many end-use sectors – including transportation, buildings, industry, and agriculture – and there are promising opportunities for AI to accelerate decarbonization in each. Examples include optimizing planning for electric vehicle (EV) charging networks, enabling virtual power plants, generating design of structural materials for manufacturing, and discovering alternatives for critical materials. Employing a portfolio of these AI-enabled solutions, while mitigating any potential risks, can support transformations needed across the economy to tackle the climate crisis, reduce costs, and improve lives.

AI applications for energy hold the promise of both great opportunities and potential risks – widespread deployment of AI requires thoughtful consideration of societal impact. Careful consideration of how AI deployment affects different stakeholders and industries can mitigate downstream risks or unforeseen hazards – for example, AI itself may lead to significant load growth that adds burden to the grid. Additionally, AI should be both equally accessible by all – including equal access to workforce opportunities in this growing industry – and designed so it doesn’t cause disparate harms. The Department of Energy (DOE) is committed to the safe, secure, and responsible deployment of AI for the clean energy economy along these principles.

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Introduction

The United States' extensive, reliable power grid has fueled the nation's growth since the early 1900s, however, today's grid does not have the attributes necessary to meet the demands of the 21st century and beyond. While today's grid primarily moves electricity in one direction from large, centralized power plants to electricity customers with relatively little information exchange, the grid of the future will manage multi-directional flows of energy and information across a diverse set of grid-connected resources. Across the bulk power system, large, centralized power generators are, to varying degrees, being replaced with smaller, distributed, and variable generators like solar photovoltaic (PV) and wind turbines, creating a need for optimizing and fast-tracking the deployment of new grid infrastructure and developing tools to better forecast and manage intermittent, non-dispatchable power plants. Across the distribution network, electricity customers are becoming active participants in grid dynamics by means of millions of grid-connected devices (e.g., behind the meter renewable generation, batteries, smart thermostats, smart appliances, EVs). These devices empower electricity customers to generate, sell, store, and optimize their own electricity use profiles and create huge opportunities for balancing more intermittent renewables and improving resiliency to weather and climate-related shocks.

This development of a clean, modern, and decarbonized grid is key to the broader move to a net-zero emissions economy. Clean energy represents a $23 trillion global economic opportunity, essentially a new industrial revolution. The strategy for building a clean energy future in the United States rests on four legs: (1) making the United States the irresistible nation for investing in clean energy; (2) ensuring that those investments provide economic and clean energy benefits in the communities that have been left behind; (3) strengthening America's workforce so that our workers have the skills they need to compete in this global clean energy market; and (4) with cutting-edge research and development (R&D), supporting industry so that each future generation of clean energy technology will be more innovative than the last.[4] AI can directly support each of those initiatives and enhance efforts already underway.

Apart from the economic incentive, we must address the impacts of climate change that are already being felt in the United States and around the world and are becoming more frequent and intense over time. In 2023, the United States experienced 28 weather and climate disasters that each caused over $1 billion in damages, collectively accounting for loss of hundreds of lives and $93.1 billion in total damages.[5] The global target specified in the Paris Agreement[6], supported by the United States, is to limit warming to well below 2°C, with the aim for 1.5°C. The Intergovernmental Panel on Climate Change (IPCC) forecasts that to meet the 1.5°C goal, the world will need to reduce emissions—from the baseline of 2010 levels—by 43% by 2030.[7]

The time is now for decisive and accelerated action, and the United States is boldly tackling the climate challenge, as described in The Long-Term Strategy of the United States.[8] President Biden has set climate goals to reduce GHG emissions 50-52% below 2005 levels in 2030, achieve carbon pollution-free electricity by 2035, and reach net-zero emissions by no later than 2050. Further, the United States has been clear that achieving these and other climate goals must simultaneously deliver against other critical priorities, including providing reliable and affordable electricity to all Americans, promoting equity and environmental justice, strengthening our economic competitiveness, creating high-quality jobs, and growing our energy independence.

This confluence of change across the electric power system is driving a need for massive innovation in the way we build out and manage the electric grid of the future. This innovation will be driven by technology that can transform vast amounts of information into actionable, decision-making capabilities. Huge advances in AI in recent years present an unparalleled opportunity to accelerate innovation across every aspect of the clean energy transition. It will also be critical to supporting the clean economy more broadly. AI can provide powerful tools to help achieve the goal of a net-zero emissions economy. The Federal Government, in strong partnership with industry, academia, and the public, can help pursue AI proactively and responsibly.[9]

This report was prepared pursuant to the E.O. on the Safe, Secure, and Trustworthy Development and Use of AI (14110), issued October 30, 2023. Section 5.2(g) directed the Secretary of Energy to take certain actions within 180 days "to support the goal of strengthening our Nation's resilience against climate change impacts and building an equitable clean energy economy for the future" in consultation with "the Chair of the Federal Energy Regulatory Commission, the Director of OSTP, the Chair of the

Council on Environmental Quality, the Assistant to the President and National Climate Advisor, and the heads of other relevant agencies as the Secretary of Energy may deem appropriate." Among those actions was to "issue a public report describing the potential for AI to improve planning, permitting, investment, and operations for electric grid infrastructure and to enable the provision of clean, affordable, reliable, resilient, and secure electric power to all Americans."

In preparing this report, DOE convened subject-matter experts from across relevant Departmental offices and the National Laboratories. DOE and the White House Office of Science and Technology Policy (OSTP) held a series of workshops with external stakeholders representing academia, industry, and non-governmental organizations to further develop AI use cases for the energy sector and identify current trends and concerns. The public was invited to provide comment on the development of this report via a Request for Information (RFI) published in the Federal Register[10].

The report is organized into five sections. Section 2 focuses on AI applications to improve grid planning, permitting and siting, operations and reliability, and resilience. Section 3 examines AI use cases that can support other portions of the economy that are also crucial to achieving a fully decarbonized power sector. Section 4 outlines additional considerations for the broad deployment of AI, including the increased energy requirements of using AI, the concerns of AI exacerbating existing biases (including racial, gender, and other biases), the potential for AI to address energy equity and environmental justice, the workforce needs and implications of AI deployment in the power sector, and the need to ensure the security and robustness of any deployment of AI in critical energy infrastructure. Section 5 presents the conclusion and key takeaways.

1.1 What is Required to Achieve 100% Clean Electricity?

The Administration has set goals of achieving a 100% clean electricity system[11] by 2035 and net-zero emissions economy-wide by 2050. The deployment of clean electricity generation required to transition the power sector to 100% clean electricity by 2035 is achievable – but unprecedented. Passage of the Bipartisan Infrastructure Law (BIL) in 2021 and the Inflation Reduction Act (IRA) in 2022 is driving huge progress towards achieving the Administration's goals. DOE found that the IRA will help drive 2030 economy-wide GHG emissions to 40% below 2005 levels, and that the combination of these laws could get the United States to 80% clean electricity by 2030, if they are fully implemented.[12] But more Federal, state, and local policy actions will be necessary to ensure full implementation of BIL and IRA and to achieve these goals and their benefits.

At the beginning of 2024, the total electric generation capacity in the power sector was approximately 1,150 gigawatts (GW). Approximately 700 GW of that capacity was from fossil fuel generation, with just under 450 GW of capacity from non-emitting wind, nuclear, solar, hydropower, biopower and geothermal, and storage.[13] Depending upon the scenario, achieving a 100% clean power sector by 2035 is estimated to require between 3,000-3,500 GW of total generation capacity.[14] The substantial increase in capacity is necessary because of increasing electrification and power demand, and the lower capacity factors of variable renewable generation. Transitioning to a net-zero emissions economy by 2050 requires electrification of many more sectors such as light, medium, and heavy-duty vehicles; residential and commercial heating systems and appliances; and industrial processes such as steel and cement production. These transitions, along with the onshoring of manufacturing, will drive substantial increases in demand for electricity.

As a result, a 100% clean electricity system in the United States is estimated to need between 2,100 and 2,500 GW of utility-scale wind, solar, and battery storage (compared to current capacity at the beginning of 2024 of approximately 270 GW). The clean grid will also need 900 – 1,100 GW of firm, dispatchable generation capacity.[15] Depending upon the scenario, that firm dispatchable capacity will need to be some combination of expanded nuclear generation, expanded geothermal generation, green hydrogen used in hydrogen combustion turbines, fossil fuel generation with carbon capture and storage (CCS), fossil fuel generation without CCS but with sufficient negative emissions technologies (e.g., biomass combined with CCS or direct air capture) to offset any fossil fuel emissions, and some other yet-to-be-identified long-duration energy storage technology.

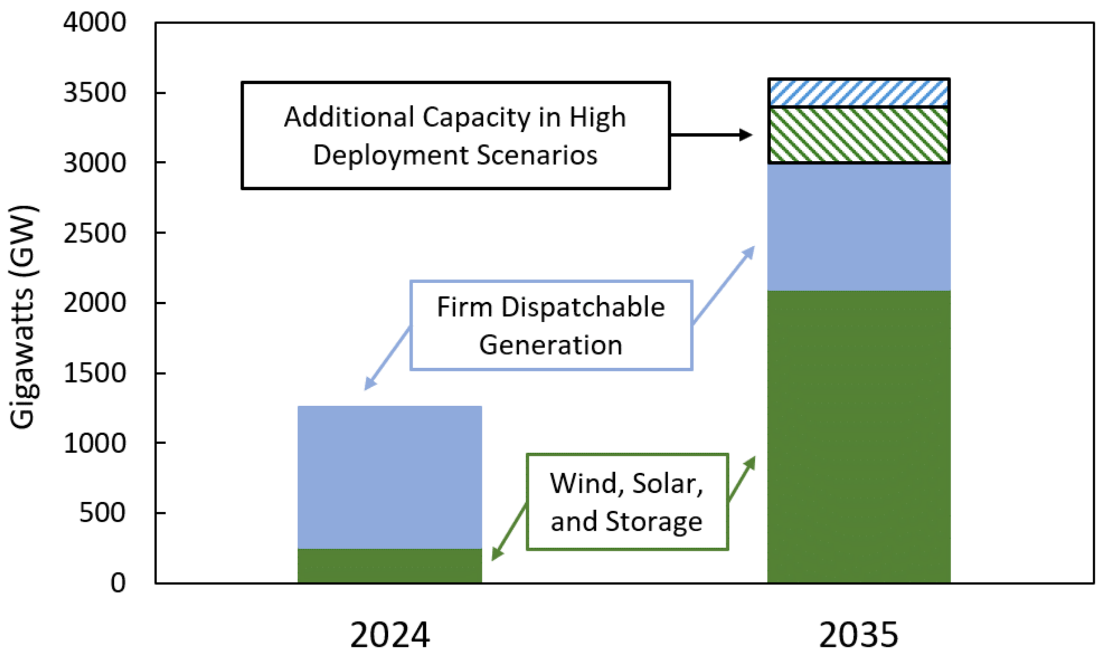

Figure 1. 2024 Generation Capacity Compared to 2035 from NREL 100% Clean Study

In 2023, DOE issued a report that identified 10 key actions necessary to transition to 100% clean electricity while maintaining or enhancing reliability and affordability.[16] The 10 key actions are:

1. **Maintain existing clean generation and storage fleet and increase flexibility where appropriate.** Currently clean generation sources (wind, solar, hydropower, and nuclear) produce approximately 40% of the electricity in the United States. Nuclear and hydro provide the majority of firm, dispatchable clean electricity. Safely and economically ensuring these existing resources continue to produce clean electricity will reduce overall deployment needs.

2. **Rapidly increase deployment of established clean generation and storage technologies.** The exact mix of clean generation technologies necessary to achieve a 100% clean pathway varies by scenario, but studies consistently show that rapid near-term increases in utility-scale wind and solar are core components of decarbonizing the power sector. Challenges include substantially increasing the total generation capacity permitted and sited each year, reversing a trend toward more restrictive local ordinances, and reducing the time projects spend in interconnection queues.

3. **Increase options for clean generation, storage, and carbon management technologies, particularly for firm, dispatchable generation sources.** The United States needs to continue to invest in a broad suite of clean power technologies, particularly those that provide high levels of firm, dispatchable capacity, such as advanced nuclear, carbon capture and storage combined with biomass or fossil generation, advanced geothermal, expanded hydropower, green hydrogen and/or yet-to-be determined long-duration energy storage. Continued investments in research, development, deployment, and demonstration will be necessary to achieve required cost reductions for these technologies to help deliver a reliable and affordable 100% clean power sector.

4. **Plan and deploy enabling infrastructure.** Deploying the necessary levels of renewable generation at lowest cost will require substantial construction of new long-distance electric transmission lines and more advanced distribution systems. Increased transmission connections between balancing areas[17] can improve grid reliability and resilience regardless of generation source. In the longer term, additional infrastructure will be necessary to support carbon storage and to deliver new clean fuels such as green hydrogen.

5. **Proactively invest in and engage with disadvantaged and energy communities to ensure the impacts and benefits of 100% clean power are distributed equitably.** Effective community engagement and buy-in will be crucial to reaching deployment goals. In particular, early attention and engagement with disadvantaged and energy communities can support deployment goals and avoid repeating the inequitable historical impacts of energy development.
6. **Augment planning, operations, and markets to enable 100% clean grids.** Operating a 100% clean electricity grid, which will include intermittent, non-dispatchable, inverter-based generation and distributed energy resources, requires updating how we plan, operate, and price electricity markets to preserve grid resilience and operational capacity.
7. **Ensure system security and resiliency as new technologies and threats emerge.** The transition to 100% clean electricity will be occurring during a time of increasing extreme weather events induced by climate change and of changing threats from cyber and physical attacks on the grid. The clean grid must be designed and operated to be secure and resilient in the face of these risks.
8. **Dramatically accelerate electric energy efficiency and demand flexibility.** Improved energy efficiency and electricity demand responsiveness are key strategies to achieve a 100% clean grid. Load responsiveness and demand flexibility (including from electric vehicle infrastructure) can reduce peak demand and reduce the need for additional generation resources and more costly transmission investments.
9. **Strengthen domestic manufacturing capabilities and develop resilient and sustainable supply chains.** Onshoring of manufacturing of clean energy technologies, as well as improving the capacity of the United States to produce and process critical minerals domestically, will support a reliable and affordable clean power sector.
10. **Equitably expand the United States clean energy workforce.** Workforce needs could constrain the pace of deployment of some clean energy infrastructure unless proactive solutions are pursued. The clean power sector will rely on a variety of technologies that can take advantage of the existing skill sets of workers in the fossil fuel sector and provide new jobs in energy communities.

Building the clean energy economy while simultaneously modernizing and bolstering the power grid will be one of the most significant challenges faced by society. The United States has established the frameworks and vision for success, but new tools and resources are needed to enable collaborative work to proceed quickly and safely.

1.2 How AI Can Enable a Clean Energy Economy

The energy industry has long leveraged AI for a variety of uses. One common subfield of AI is machine learning (ML), which involves teaching machines to learn from data without being explicitly programmed. ML models have been used by researchers and the energy industry to glean value from vast pools of data available through the power grid's existing distributed network of sensors, meters, and plants. In addition to ML expert systems and logic-based systems also fall under the umbrella of AI and have a similarly significant history of development and deployment. DOE has been a supportive partner working with the industry to build a vision for the smart grid of tomorrow[18] and, through the National Labs, supporting continued R&D of AI models for scientific and energy applications.

EO 14110 Definition of Artificial Intelligence

The field of artificial intelligence (AI) has a long intellectual history, with a broad variety of models and approaches developed over time. EO 14110 and United States Code defines Artificial Intelligence as:

…a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. Artificial intelligence systems use machine- and human-based inputs to perceive real and virtual environments; abstract such perceptions into models through analysis in an automated manner; and use model inference to formulate options for information or action" [3].

Recent advances in AI capabilities vastly widen the span of use cases for AI across the energy industry. Over the past several years, a new class of AI models has emerged – generally referred to as foundation models.[19] These AI models, built off a model framework known as "deep learning," are trained on broad data, generally using self-supervision, and are applicable across a wide range of contexts. As compared to previous AI models, which were generally optimized for specific types of problems, foundation models can be adapted to a wide variety of tasks. Foundation models, however, also have well-known weaknesses including that they have stochastic outputs and can produce hallucinations—outputs that seem authoritative but are factually incorrect. To fully unlock the potential of such models these risks will need to be mitigated in the application of foundation models.

This report lays out the transformational opportunities presented by foundation AI models, in tandem with continued integration of mature AI technologies, to reimagine how we build, manage, and operate power grids and energy systems and accelerate clean energy demonstration and deployment. This will support the United States in achieving the Administration's goals of achieving a 100% clean electricity system by 2035 and a net-zero GHG emission economy by 2050 while maintaining and growing America's edge in scientific innovation.

The table below outlines a summary of the opportunities presented in this report.

Table 1. AI Opportunities for a Clean Power Grid and Clean Energy Economy

Clean Power Grid	
Planning	• Completing, correcting, and harmonizing sparse data on grid infrastructure to inform predictive asset replacement • Assessing dynamic system conditions to inform upgrades, maintenance, and new resource needs, as well as dynamic assessments of available grid capacity • Preventing avoidable losses through predictive maintenance • Detecting faults in solar panels, dams, wind turbine blades, generators, etc. • Processing aerial images for remote job-site inspections • Informing adoption of grid-enhancing technologies (e.g.., Dynamic Line Rating to provide real-time transmission and distribution conditions; Topology Optimization to reroute power flow to reduce congestion) and accelerating interconnection queues to get projects connected to the grid • Enabling modelling for distributed energy resource adoption to anticipate distribution system upgrades and implications for load, and load shape
Permitting and Siting	• Organizing, extracting, consolidating information across Federal, state, and/or local regulations to improve the efficiency of administrative processes • Accelerating environmental review process, e.g., for comment processing, information extraction, drafting documents, automating compliance checks, etc. • Optimizing placement of renewable energy and transmission projects to facilitate effective and efficient siting and permitting • Generating size/location data for rooftop solar panels, optimal placement of wind turbines, etc. • Identifying and managing sites for geothermal energy, using satellite imagery and seismic data • Placing hydropower dams in a way that satisfies energy and ecological objectives

Clean Power Grid	
Operations and Reliability	• Improving variable renewable energy forecasting (solar, wind, run of river hydro) • Improving demand forecasting using AI trained on historical data, including weather, climate, economic and load • Improving power system optimization; reducing the computational intensity of modeling • Setting real-time pricing to optimize the operation and/or economics of distributed energy resources, storage, etc. • Anticipating system anomalies to avoid disruption
Resilience	• Enabling proactive monitoring to make critical infrastructure more resilient to severe weather • Monitoring, detecting, and diagnosing anomalous events (e.g., extreme weather events, cyber-attack) • Improving coordination with other interdependent systems (e.g., natural gas, water) to regain operation after disruption • Enhancing situational awareness across system with coupled AI and digital twins • Improving the accuracy and interpretability of landslide predictions, sea level rise, storm surge, etc. • Simulating disruption/disaster scenarios to inform resilience strategies • Enhancing system efficiency and coordination to restart the grid during full or partial blackouts • Optimizing the deployments of repair crews to accelerate response • Identifying the fastest path to system restoration

Clean Energy Economy	
Transportation	• Optimizing electric vehicle (EV) charger planning, permitting, and siting • Optimizing EV charger usage and pricing for a variety of customers to balance user charging preferences and grid load • Enabling vehicle to grid operations and providing grid services through EV or electric vehicle supply equipment (EVSE) assets • Enabling EV fleet coordination through vehicle to vehicle and advanced charging

Clean Energy Economy	
Buildings	• Unlocking Virtual Power Plant adoption through improved customer segmentation and incentive allocation • Drive materials innovation in building materials e.g. low carbon cement • Optimizing energy use in buildings (for occupant comfort, for grid integration, to learn behavior, etc.) • Modeling buildings to predict energy, load shape, appliance disaggregation, future consumption, and coordination with power system • Coordinating demand response programs, the internet of things, smart appliances, distributed energy resources, etc. • Optimizing HVAC performance and operation to energy efficiency and/or demand response priorities • Estimating marginal emissions factors, providing customers feedback about energy & emissions, suggesting behavioral interventions • Leveraging AI and digital twins to optimize operations and resilience across the built environment
Industrials and Manufacturing	• Improving manufacturing quality control and better sort feedstocks for recycling streams • Reducing carbon footprint of industry, data centers by optimizing energy consumption, cooling, etc. • Revolutionizing component design through generative inverse design, particularly when paired with advanced manufacturing techniques • Optimizing predictive maintenance and operations optimization to improve manufacturing efficiency and performance
Agriculture	• Optimizing colocation of renewable energy with agriculture for synergistic benefits (e.g. agrivoltaics) • Supporting bioeconomy and biomanufacturing R&D • Using deployable field sensors and satellite imagery to better map and predict agricultural yields • Optimizing precision agriculture and delivery of fertilizer and water to crops

Clean Energy Economy	
Cross-Cutting Themes	• Identifying methane leaks and reduce emissions from the oil and gas sector • Driving materials innovation, identifying material substitutions, and enhancing recycling technologies • Mapping and modeling the subsurface, which is critical for identifying opportunities for hydrogen and carbon storage • Optimizing power plant, industrial, and built environment parameters to reduce CO2 emissions • Using sensor and/or satellite data to proactively suggest pipeline maintenance and/or detect existing leaks • Synthesizing, characterizing, modeling, and designing materials; accelerating materials discovery • Guiding experimental design and monitoring physical processes of new technologies (e.g. fusion, batteries, electrocatalysts, etc.) • Identifying and managing storage sites for CO2 sequestered from power plants and industry • Improving understanding of subsurface (geohazard prediction, land use decisions, groundwater & mineral discovery, geothermal, etc.) • Estimating the state of the system when there are few sensors, improving data-efficiency for low-data settings

Foundation models hold substantial promise for uses beyond text and image processing and generation featured in commercially available models. The application of foundation models within the power industry, however, must be approached with caution. The power grid is critical infrastructure - mistakes can cause significant economic damage, impact marginalized populations, and destroy long-built trust in grid operators. To effectively integrate AI into the power industry, the following prerequisites as listed in Table 2 are essential.

Table 2. AI for Power Grid Requirements

Category	Description
Rigorously Validated Systems	The models and data sets used for AI training must be thoroughly validated for accuracy through extensive testing in simulated environments that replicate real-world scenarios. This validation is critical to ensure AI's reliability and safety when applied to power grid operations.
Physics-Informed and Explainable	AI outputs must be consistent with the fundamental laws of physics to provide realistic, explainable, and applicable solutions. Physics-informed AI models, such as those that accurately simulate the flow of electricity through the grid, can lead to more efficient and reliable energy distribution.
Human-in-the-Loop (HITL)	Human oversight should be an integral part of AI-driven processes to ensure ethical, practical, safe, secure, and innovative outcomes. Human-in-the-loop approaches involve human expertise and accountability in the decision-making loop, allowing operators to review and refine AI-generated recommendations.

Category	Description
Scalability and Performance	Considering the rapid expansion of edge devices (e.g. devices at the boundary between the utility equipment and the customer's equipment) and the increasing demand for electrification, AI needs to efficiently handle and process large volumes of data (or system of systems) in real-time or near-real-time to effectively inform operational decisions.
Ethics and Governance	AI systems in the power grid should comply with robust cybersecurity policies and standards due to the critical nature of electric infrastructure. Adherence to frameworks like the NERC Critical Infrastructure Protection standards is necessary to mitigate cyber threats and maintain the integrity of grid operations. AI systems should also consider the principles of Ethically Aligned Design.

2. AI to Improve Grid Planning, Permitting, Reliability, Resilience, and Security

2.1 Grid Planning

The power grid is one of the largest machines ever built. Despite its size and complexity, grid planners must continue to shape the growth of the power grid to ensure that every user can connect to the power grid, that sufficient generation exists to meet load, and that generation can reach loads. A 100% clean power grid will require a significant amount of new infrastructure, both in terms of new clean energy generation and the rise of distributed energy systems. AI can help lower the amount of new build-out required to reach a 100% clean grid by unlocking underutilized assets, improving coordination and optimization of new infrastructure, and by synthesizing the vast and diverse types of technical data needed through foundation models.

2.1.1 Capital Allocations and Planned Upgrades

Accurate system knowledge is critical to developing cost-effective strategies for maintaining, modernizing, and expanding grid capacity to meet our future energy needs. Having accurate information on grid infrastructure enhances utility or system operator insight into capacity, maintenance, and end-of-life constraints to continued system function. Without such awareness it is not possible to efficiently plan the systemic and capital-intensive infrastructure projects necessary to expand system functionality and meet evolving requirements.

Industry practice commonly employs a maintenance paradigm for capital allocation, wherein expenses associated with like-for-like replacement of worn-out grid assets are easily justified and incorporated into the rate-base while costs for adding capacity are more typically allocated to new sources or loads. This biases the pool of available capital towards like-for-like infrastructure replacement projects that perpetuate grid status quo rather than modernizing and expanding the system. Quantifying the systemic functional and economic benefits to justify the expense of a planned technology deployment or facility expansion requires detailed knowledge of system assets, but the earliest grid components were built more than a century ago and the long-lived nature of grid assets means most of the existing grid infrastructure in the United States predates modern information management systems.

The decades-long and heterogeneous transition from analog to digital information management systems across thousands of electric utilities and millions of individual grid assets placed in service across numerous technological epochs makes achieving data transparency for grid infrastructure a complex challenge. Detailed geospatial, functional, or configuration data for system assets may not exist, and even when it does, a history of undocumented maintenance and upgrades performed during power outages or other emergency conditions may render the data inaccurate. Available data may also suffer from completeness or formatting issues that can render the information unusable.

AI techniques could be employed to complete, correct, and harmonize sparse data on grid infrastructure, or to validate existing datasets through complementary information. This would allow utilities to employ predictive asset replacement to leverage economies of scale that are not realized through the existing maintenance paradigm. It would also allow utilities, regulators, customers, and other stakeholders to better assess system conditions and evaluate the benefits of strategic upgrades to system capacity or specific technology investment.

2.1.2 Improved Information on Grid Capacity

Traditional grid capacity modeling uses peak load and peak transmission capacity, with generous safety factors. This static picture of grid capacity, while operationally straightforward, lowers utilization rates of existing infrastructure assets. AI presents an opportunity to construct a more dynamically resolved picture of grid capacity to accelerate the integration of intermittent clean energy sources and address new load growth. In particular, AI can support the adoption of several grid-enhancing technologies (GET).

The first is dynamic line rating (DLR),[20] which adjusts line capacity based on external conditions such as wind speed and temperature, rather than considering a static line capacity. DLR enables transmission operators to run higher current through existing transmission, which can ease bottlenecks and enable more interconnections. DLR can be particularly impactful for variable renewable energy sources whose output is correlated with higher line ratings, e.g., wind energy output and higher DLR are both tied to higher wind speed. AI can support DLR through improved forecasting of local and regional weather.

Another GET to increase utilization of existing grid assets is topology optimization (TO), which reconfigures the grid topology through opening and closing circuit breakers, to allow higher utilization rate of grid assets. Identifying the right set of actions for topology optimization is often challenging and constructed as constrained, multi-objective optimization functions. AI can help identify solutions under a variety of scenarios for topology optimization, helping reduce costs for interconnection and customers.

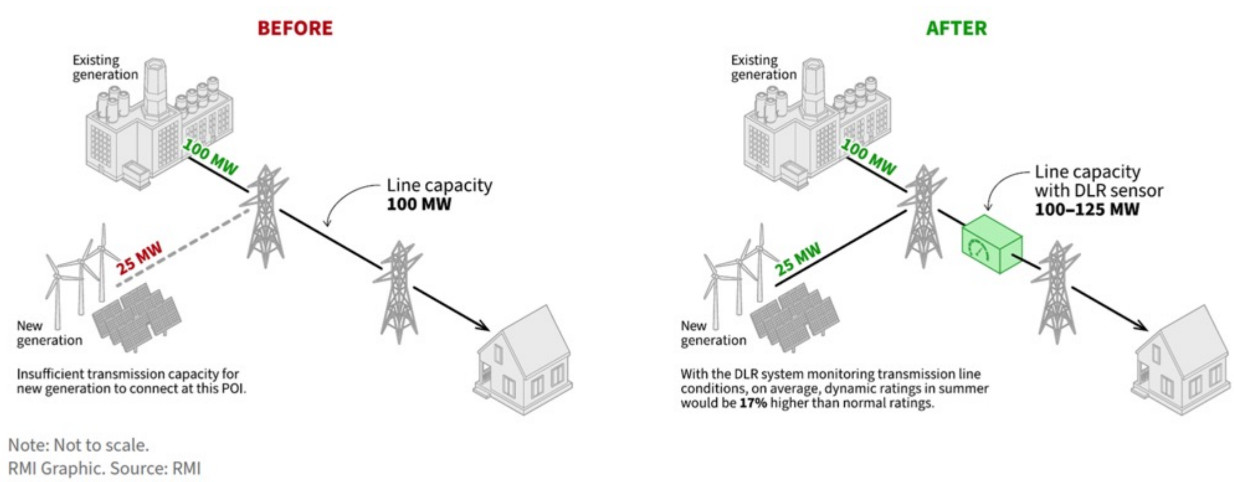

Figure 2. Topology Optimization Enables Greater Interconnect with Existing Grid Assets[21]

2.1.3 Improved Transportation and Energy Planning Alignment

The complementary rise of distributed energy systems and aggressive load growth presents a new challenge for load forecasters and grid planners. Distributed energy systems have shifted both generation and loads from centralized, utility-coordinated industrial sites to being integrated into residential and commercial areas, with varying levels of visibility from grid planners. The most significant distributed load arises from EVs and associated chargers, which can require electrical infrastructure upgrades, if not strategically installed and utilized.

AI can make alignment between transportation and energy planning systems more efficient and scalable in several ways. First, grid operators, utilities, and utility regulators can leverage AI to enhance modelling for distributed energy system adoption and its impacts on the required grid upgrades. For instance, the 2023 California Public Utility Commission (CPUC) Electrification Impact Study used ML to predict user adoption of EVs, EV chargers, rooftop solar, energy storage systems, and other distributed energy systems and model their impacts on hourly, user-level demand profiles.[22] AI can also be used to optimize the placement of EV charging infrastructure, to minimize grid infrastructure upgrades needed while still maintaining equitable access and availability, which all help to lower the cost of electrification.[23] Finally, AI methods like reinforcement learning can also be used at the EV charger level to adjust price signals in response to grid congestion and reduce demand spikes in load from EV charging sites.[24]

2.1.4 Interconnection Issues and Power Systems Models

Interconnection queues have become a major bottleneck to clean energy deployment as the median time to progress from an interconnection request to commercial operation has increased from less than 2 years at the beginning of this century to five years in 2022.[25] This increase in processing times has coincided with a substantial increase in the number and capacity of utility-scale generation projects (including battery storage) requesting interconnection. The number of interconnection requests averaged approximately 300 per year from 2000-2004, increasing to approximately 850 per year from 2005-2014 steadily increasing since then to more than 3,000 requests in 2021 and 2022.[26] At the end of 2022 there were over 10,000 projects in interconnection queues totaling over 2,000 GW of generation and storage capacity.

With the rapid increase in the number of projects requesting interconnection and the adoption of renewable energy resources, energy storage, and other modern grid elements, the complexity and computational demands to perform interconnection studies performance of existing power-flow modeling tools has become increasingly inadequate to tackle large-scale planning and operational problems for the grid.[27] Transmission providers have made strides to improve the software they use and employ greater automation of their interconnection processes. But these strides have not kept pace and many of the modeling tools used require substantial manual inputs and specialized expertise to produce results.

Updating grid-modeling software, including greater automation of interconnection studies, and interconnection application processing, has been identified as a priority area for improving interconnection times.[28] AI can help accelerate both the modelling side and application compliance.

Improved models that make use of improved physics-based optimization algorithms can substantially reduce the actual time required to produce results from models and enable more scenarios to be dynamically evaluated.[29] Additional progress could be made by developing AI surrogate models for the grid that could model dozens or hundreds of scenarios of grid development during feasibility studies. Foundation models, such as Large Language Models (LLMs) and Large Multimodal Models (LMMs), could also play a role by automatically screening and validating unstructured data in applications (e.g. documents pertaining to land ownership) substantially reducing the time it takes for the dozens of applicants in a given study to perfect their applications.

Transmission providers and software developers are beginning to deploy newer models, but substantial work remains to further test and validate models, improve data transparency and sharing (while protecting security and privacy), and coordinate studies with dozens of interested parties.

2.1.5 Challenges, Accelerating Development and R&D Needs

Grid planning is a key area that is ripe for AI-enabled innovation. While the industry has traditionally used static, peak-based planning, higher penetration rates of variable renewable energy and distributed loads are creating a surge of data that both challenges conventional modelling and creates value-add opportunities for AI. However, integrating AI into grid planning will require new standards for planners and regulators to adapt. Regulators will need to both incentivize utilities to leverage AI to increase utilization of existing assets, rather than build new capital projects, and ensure utilities are adopting safe, trustworthy, and secure AI platforms. Transmission operators and utilities will need to continue to digitize their operations and break down data silos while preserving customer privacy and ensuring the security of electric infrastructure.

Finally, DOE has a significant role to play as a key convener for the energy industry, as a funder of power grid R&D, and as a leader in innovation in partnership with the National Labs. Already, DOE has invested significant effort in building a smarter grid powered by AI, including through the Grid Modernization Initiative,[30] the ARPA-E Grid Optimization challenge,[31] and various other funding opportunities for smart grid.[32]

2.2 Siting and Permitting of Clean Energy Infrastructure

Deploying clean energy infrastructure at the scale and pace needed to meet decarbonization, affordability, reliability, and resilience objectives will require improvements to how such projects are planned, sited, permitted and connected to the grid.[33] A 2023 survey found developers of utility scale wind and solar projects cited local zoning ordinances, grid interconnection, and community opposition as the leading causes of project delay and/or cancelation.[34] Previous studies have shown that permitting timelines are a key sensitivity driving deployment cost for geothermal energy,[35] distributed rooftop solar,[36] and critical minerals mining.[37]

Foundation models such as LLMs, and LMMs, as well as other AI models, have the potential to make substantial improvements in siting and permitting processes. Models can be fine-tuned to the relevant contexts for these processes that can be used to build tools for developers, government reviewers, and the public that can improve the design of projects, bring efficiencies to siting and permitting reviews, and improve public engagement and satisfaction.

Deploying LLMs and similar foundation models to directly support government decision-making will require substantial caution, research, and validation, given the well-publicized limitations of these models (including their propensity to produce authoritative sounding but inaccurate information), concerns about bias, and potential cost of wide deployment.

2.2.1 Overview of Near-Term AI Use-Cases in Siting and Permitting,

In the short term, AI-powered applications are being developed for specific, discrete use-cases and workflows. In addition to generating text, LLMs are more adaptable than traditional Natural Language Processing (NLP) models and can be adopted for common language processing tasks such as sentiment analysis, text classification and named entity recognition. LLMs can be incorporated into compound models that can begin delivering substantial value in improving siting and permitting processes immediately in certain specific use cases. Examples include:

i. **Bulk Data Extraction and Organization.** Other than the timelines developed from studying interconnection processes and the completion times for Federal Environmental Impact Statements under the National Environmental Policy Act (NEPA), there does not exist a comprehensive, publicly available dataset of project development timelines, nor of the characteristics of projects.

LLMs can be used to extract and organize unstructured data contained in the text of past permits, approvals, and environmental reviews into useful structured data that could be used in a variety of research contexts.

ii. **Process Improvement.** Structured data from past environmental reviews could be analyzed by foundation models, other AI systems, or traditional statistical methods to link key performance indicators that may be able to provide insights into how to achieve a more efficient and more effective environmental review process. For example, this structured data could be used to determine what project characteristics may correlate with longer permit review times and/or longer overall development timelines; to improve mitigation measures and environmental outcomes; and to identify and predict trends in changes to local ordinances relevant to clean energy deployment (among other things).

iii. **Comment Processing.** Government agencies and private contractors have used a variety of NLP algorithms to assist with processing public comments received on environmental documents (and in regulatory settings) for a decade or more. Such algorithms can identify duplicate documents, conduct sentiment analysis, and identify comment topics.[38] An application with current (and future) LLMs could further improve upon existing models LLMs may allow customizing and fine-tuning through no-code or low-code methods that could be done by subject matter experts with less support from technical experts.

iv. **LLM Co-Pilots with Retrieval Augmented Generation (RAG)**. One of the leading approaches to improve the accuracy of LLMs and curate their knowledge base is to pair them with a retriever that can draw information from a curated set of documents and data. This RAG method has been deployed in a variety of settings. It has also been deployed in consulting firms, law firms, and medical settings with the AI models acting as digital research assistants to subject matter experts.

v. **Automated Application Completeness Checks**. There is anecdotal information that in a variety of processes (e.g., permitting, siting, environmental review, or interconnection applications), significant delays can occur at the very beginning of the process as an applicant is completing their applications and providing all the information required for expert agency staff to conduct a review. For simple online applications where an applicant submits information into predefined forms, it is relatively straightforward for immediate feedback on whether all cells are filled in or if the information provided fits within certain pre-defined parameters. AI models make it possible to provide similar immediate completeness feedback for technical drawings or for long, text-based submissions (such as environmental resource reports).

vi. **Designing Training Modules**. Research to date indicates that performance improvements from using LLMs are most pronounced for less experienced workers. Foundation models could be used to create more responsive and individually tailored training modules (including ongoing use of the tool as a digital assistant) to improve the efficiency and performance of new permitting staff. This will be particularly relevant in a context where Federal agencies are trying to hire hundreds of new staffers and encountering difficulties in finding enough qualified applicants and/or where state and local authorities have limited resources and in-house expertise.

These different general AI uses will likely be applied slightly differently depending on the setting. Most siting and permitting for renewable generation capacity (including battery storage) and transmission occurs at the state and local level. These processes typically are focused on interpretation of zoning ordinances and building codes. Projects that will require Federal approvals include those that occur on Federal lands, those that receive Federal funding (such as grants or loans from DOE, EPA, USDA, etc.), those that potentially affect endangered species or other federally protected resources, and transmission lines that may be subject to Federal backstop siting authority. Much of the focus on improving reviews at the Federal level is on improving reviews required under the National Environmental Policy Act (NEPA), the Endangered Species Act (ESA), the Clean Water Act, and the National Historic Preservation Act (NHPA).[39]

The use of AI in government functions such as siting and permitting will require particularly careful vetting, validation, and trustworthiness. Even as foundation models improve in accuracy and trustworthiness, additional consideration will need to be given to whether and how such models could help meet statutory requirements requiring expert judgment from agencies, such as making conclusions about whether environmental impacts in a NEPA review are “significant” or whether an action will jeopardize the continued existence of a species as that is listed under the ESA.

2.2.1.1 State and Local Siting and Permitting

Some of the key challenges for permitting and siting at the state, local and tribal level include:

- state and local authorities must review new technologies (EV chargers, battery storage, utility-scale wind and solar) for projects about which they have little past experience;
- generally limited resources for many local authorities;
- managing effective local community engagement;
- developers must navigate permitting rules (and at what level of government those rules are enforced) that are different from state to state and from local authority to local authority.

AI tools can be developed that substantially improve the capacity of state, local, and tribal authorities. Private companies are beginning to provide AI-powered software products for project developers that provide better insights on zoning ordinances and permitting processes, incorporate predictive algorithms on whether zoning ordinances are likely to be made more restrictive, and provide better insights on how developments fit long-term community development plans to inform better community engagement.

Additional tools can be developed that leverage data sources on environmental justice and energy equity that would enable better early planning of projects to contribute to improving both. AI applications can be developed that would provide resources for permitting authorities to understand the newer technologies and how other jurisdictions have developed best practices for their permitting.

An area where AI can provide a solution is in automating certain portions of local permitting processes. Many developments that require state and local review are "as of right" where the property owner or developer is allowed to build so long as the project meets certain pre-defined characteristics outlined in a zoning ordinance or building code. Although developers already have the right to build these projects, significant time is still spent by local officials reviewing and verifying project characteristics. These reviews could be automated through software and, indeed, many jurisdictions have started to adopt automated processes for the simplest types of projects.

For projects that have a variety of overlapping requirements from different parts of the ordinance or code, the complexity of those relationships, and the need to program each of them explicitly, quickly becomes too burdensome and onerous. Logic programming is a deterministic form of automated reasoning that is distinct from other types of AI models discussed in this report that may be more suitable for automating complex permitting processes – so long as the permitting requirements are clear and consistent. In jurisdictions with limited resources, this could save staff time in processing applications to determine if basic requirements are met and allow staff to focus on more complicated issues and/or on inspection and verification. There are examples of private companies already providing automated permitting services to jurisdictions with computer apps built on logic programming.

2.2.1.2 Federal Reviews

One constant process across Federal agencies regardless of their specific permitting authorities are the reviews conducted under NEPA and other statutes such as the NHPA, ESA, and Clean Water Act. Improving NEPA and related reviews receive substantial attention at the Federal level and AI has the potential to make considerable improvements to these reviews as outlined in Section 2.2.1.

The first step in building effective, reliable, and transparent AI-powered tools to improve these processes is engaging in a comprehensive effort to make environmental analyses and other outputs from environmental review and permitting processes more accessible and machine readable. Federal reviews under these and other statutes produce millions of pages of unstructured data in the form of PDF text each year, as well as structured geospatial and tabular data. In addition to past environmental and permitting reviews, AI models would also incorporate variety of laws, regulations, ordinances, court opinions, and structured data in other formats such as geospatial data, images, and tabular data. These data sources have not generally been accessible other than by manually searching through multiple different databases maintained by different agencies. Many public documents are not readily available on the internet.

Until recently, trying to consolidate this information would have required significant staff resources to do further organizing, data-entry, working through compatibility problems between different databases, and different computer systems and file formats between agencies that were not interoperable. Even if a central repository could be developed, old data warehousing architectures were not optimized for AI/ML algorithms. The advances in NLP represented by the LLMs, combined with advances in the multi-modal models that can combine images, geospatial information, and tabular data, have the potential to fundamentally change the ability for federal permit reviewers to organize and understand information necessary to conduct more efficient permitting and siting processes and environmental reviews. Researchers at the University of Arizona have demonstrated some of the capability of NLP tools by developing a large database of existing Environmental Impact Statements (EISs) and using NLP to develop more metadata about the documents, including geotagging them to the county level, enabling improved search and accessibility of the documents.[40] While challenges remain in addressing the compatibility and interoperability of the existing databases across agencies, the AI-powered tools can substantially reduce the time required to consolidate and organize these disparate information sources and optimize their data structure for use with AI models.

The AI powered tools can also help improve the consistency of reviews across agencies. One of the challenges of processing the existing corpus of NEPA documents is the great variation in structure and formatting of the documents. This heterogeneity makes it difficult to compare documents from different agencies and to research and identify best practices for assessing different issues such as environmental justice and application of the social cost of GHGs.

2.2.2 AI Models' Potential to Assist Subject Matter Experts in Reviews

AI models can function to assist subject matter experts in technical reviews, provided that their risks are appropriately mitigated. For example, risks of hallucination from LLMs or multimodal models can be mitigated through development of compound systems that combine the functions of foundation models with additional AI models applied in particular workflows.[41] One of the current trends in model development is to combine multiple smaller, fine-tuned models that are focused on a specific topic area, into an agent-based workflow to improve accuracy and reduce the compute resources required.

A variety of public, AI models could be developed that are trained on curated data sets of publicly available information. The models might be focused on particular technologies, such

Spotlight: AI and Permitting

DOE's Office of Policy working with the National Laboratories has initiated a three-year pilot project with multiple workstreams to assess using foundation models and other AI to improve siting, permitting, and environmental review processes.

The project is exploring specific use-cases where AI applications can provide substantial efficiency gains and process improvements in a variety of contexts in Federal, state, and local reviews. It will leverage the expertise of the National Labs to rapidly prototype and test specific applications of AI that can be tested and deployed with beta-testing users across other cooperating agencies. The work will also develop and validate new benchmarks, methodologies, and protocols for human-in-the-loop testing that will be crucial to developing trustworthy AI.

The pilot project to date has focused on developing the data processing pipelines necessary to convert unstructured data from PDF documents into open and direct access data formats that are optimized for use with foundation models and are not locked into proprietary database architectures. The pilot project will assess the suitability of commercial AI models in permitting workflows versus finetuning open-source models and/or building new foundation models. It will also explore a variety of application architectures such as RAG and incorporating AI models as agents for specific functions.

The outputs of the pilot project will include validated software applications that can be further developed into production software products for use across the Federal Government as well as new public data sets and open-source code.

as advanced reactors;[42] on datasets about specific topic areas, such as the U.S. Fish and Wildlife Service ECOS database on endangered species; or on multi-topic environmental review documents, such as EIS's and environmental assessments prepare under NEPA. The models would incorporate publicly available data from some combination of past permit or environmental reviews, scientific literature, statutes, ordinances, regulations, geospatial data, data on energy equity and environmental justice metrics, and other sources. The models could then be adapted by private actors, by NGOs and community organizations, and by government reviewers at all levels.

The Federal Government can facilitate progress in this area by both developing open-source datasets and models and by rigorously testing, evaluating, and validating such models. Protocols and training for use of such models will be necessary to ensure that human users do not place too much trust in such models or use their output without further independent individual validation and exercise of professional judgment. Rules need to be developed around transparency around the use of such models and disclosures would be included in publicly released documents detailing how AI was used in the review process.

2.2.3 Challenges, Accelerating Development and R&D Needs

Data Standardization. Data standardization process results in a common format, structure, and language, which facilitates the seamless exchange and integration of information between different entities. This uniformity is particularly beneficial for agencies that need to collaborate and share resources. In addition, standardized data allows agencies to compare and analyze pertinent information such as cumulative impacts, specific purposes, and needs with greater ease and precision. When data from different sources is consistent in format, it can be aggregated without the need for extensive preprocessing, which saves time and reduces the potential for errors.

Data Augmentation. Data augmentation techniques include data enrichment, imputation, and summarization. For example, there is a need to develop additional metadata to describe the content of each document, making it easier for end users to find the information they need. These metadata including the data origin (e.g., geographical location, project types such as land management plan, linear project, type of permit, etc.), content structure of the document and other data transformation.

Distributed Data Fabric. A well-designed data fabric architecture, incorporating solutions such as data lakehouses,[43] offers numerous benefits over traditional data systems. For example, unlike traditional databases that require a predefined schema to store data, data lakehouses can store all types of data in their raw form. This will facilitate evolving the schema over time without bearing the cost of rewriting the entire database structure, as in traditional relational database management systems. A data fabric approach also allows a distributed application architecture across multiple agencies with multiple systems, facilitating high-quality data accessibility without requiring centralized storage systems. Any data fabric solution should also provide access controls, data quality checks, and metadata management to ensure that data is not only accessible but also reliable, secure, and compliant with regulation.

Fine-tuning of Foundation Models. Siting and permitting documents are typically dense with legal terms, technical specifications, and compliance-related language that require a nuanced understanding not only of the words themselves but also of the context in which they are used. These documents often reference statutes, codes, and industry-specific guidelines that are not commonly discussed in the broader web that AI models are typically trained on, making it difficult for AI models such as LLMs to draw upon a wide range of pre-existing knowledge. The decision-making process documented in these texts involves a logical structure and a level of reasoning that is specific to the field, which may not be readily apparent without a deep understanding of the domain. Therefore, LLMs need targeted training on such specialized content to accurately interpret and process the information within the context of the domain's unique requirements.

2.3 Grid Operations and Reliability

Ensuring the reliable operation of the power grid is critical to our economy and to people's livelihoods. The shift to a 100% clean energy grid, with significantly higher amounts of non-dispatchable generation, challenges the traditional paradigm of grid operations and the set of tools used to ensure grid resilience. AI offers significant opportunity to better maintain existing generation assets, forecast non-dispatchable generation and adjust flexible loads, and better inform operational safety.

2.3.1 Load and Supply Matching

The primary responsibility of electric power system operators is to balance the power supply and demand at all times. With increasing amounts of variable generation (e.g., solar and wind), operators need to rely on significantly more accurate weather forecasts to understand the impacts on both generation and load, particularly as the decline of dispatchable resources requires improved load estimation. AI can help bring significantly more powerful and high-resolution modelling to bear on these problems.

AI-based, multi-fidelity surrogate models can act as large-scale dynamic emulators with uncertainty quantification to assist grid operators and accelerate existing numerical methods-based simulation tools. The grand challenge is to obtain accurate estimations for various atmospheric variables at sub hourly resolution and at high enough granularity (e.g., down to 10-meter scale compared to the 100+ kilometers common in current climate models) that the model outputs can be used to forecast renewable generation and load demand.

AI can help not only centralized grid operators, but also benefit Virtual Power Plants (VPP) providers who aggregate various distributed energy resources with flexible loads, which can be monetized to respond to price signals from operators. AI can help optimize revenue for VPP providers while also providing customized options based on user preferences.

Finally, AI can also work at the grid edge—the boundary where utility equipment meets the customers' equipment. An increasingly digitized grid comes with a surplus of sensors and smart meters, which can potentially overwhelm grid control centers with deluge of data and increase centralization of failure modes. Deploying AI at the edge can help process raw data and even make decisions locally, with the appropriate safeguards. Edge AI processing can also improve grid resilience and grid cybersecurity by reducing the number of data connections required for grid operations.

2.3.2 Predictive and Risk-Informed Maintenance

Many electrical generation plants in the United States maintain equipment using a schedule-based approach to servicing components. While the proportion of total operating costs differ significantly between the variety of plants, each type of plant can experience moderate to significant cost reductions if maintenance strategies shifted toward a predictive or risk-informed method. Using AI and ML techniques, plants can utilize historical maintenance data and OEM equipment specifications to tailor their maintenance strategy to conform to component condition in contrast to calendar-based strategies. This application has the potential to significantly reduce labor hours needed to keep the plant operational, while also avoiding wasteful replacement of equipment when the component still has a large remaining useful life.

2.3.3 Operational Safety and Issues Reporting and Analysis

Operational event reporting and analysis provides an opportunity to measure performance of various system elements including but not limited to electric power grid systems and components. AI can be used to estimate trends of events, identify frequent issues, extract insights from reports, and identify lessons learned that can help improve grid systems reliability and safety. DOE is also investing in AI/ML to analyze and functionalize data from DOE safety and operations data.[44]

2.3.4 Challenges, Accelerating Development and R&D Needs

The power grid is a vast machine that was built out over decades and different technological eras. Grid operators regularly deal with this heterogeneity and operate the grid with an overall reliability of 99.95%.[45] Grid operators are likely to be very reluctant to adopt new technologies without robust assurance they will not compromise this reliability. To unlock the full potential of power grid data sources with AI, there first needs to be investment in a standard framework and common ontology of the power grid[46] and tools for data processing, analysis, and visualization.

Grid operations are also a highly security-sensitive application for AI tools, with data carefully guarded due to its infrastructure critical nature. Overcoming this obstacle necessitates collaborative efforts between academia, government, and industry to establish data-sharing mechanisms, fostering an environment conducive to advancing R&D – while still ensuring that necessary and appropriate security and privacy considerations are upheld. These mechanisms could look like shared data warehouse infrastructure and common performance benchmarks, including with synthetic privacy-preserving data modelled after real-world data, and ensuring access to trusted researchers. Privacy-enhancing technologies (PETs), such as federated learning where data remains with the producer and is not co-localized with the AI model, can be a critical tool when establishing frameworks for handling potentially sensitive data from the grid. See Section 4.4 for more on the subject of PETs.

More broadly, data access is a key bottleneck for VPP adoption. Developing common APIs for end-use customers to participate in various demand shaping market tools and opening up utility data for researchers and developers is also key to developing AI-enabled tools for operators and utilities, while increasing competitiveness in utility markets. As with all API development for potentially sensitive data, implementing best practices rooted in the software development principle of least privilege and role-based access control can help enable broader accessibility, while ensuring appropriate security and controls.

Finally, while significant investment has gone into consumer-facing AI applications, further investment is needed in developing physics-informed or domain-aware AI approaches[47] with uncertainty quantification (see Table 3). Providing reliability guarantees for AI models is paramount to making grid operators comfortable with integrating such AI models into workflows.

2.4 Grid Resilience

In order for the grid to function reliably, it must be resilient against a diverse array of events[48] and maintain a high standard of reliability. Even a power grid with 99% uptime would leave people and companies without power for 3.5 days in a year. As a result, building a resilient grid with multiple redundancies and rapid decision-making to identify anomalies is key. AI, with its ability to rapidly ingest vast amounts of data and identify subtle shifts in data distributions, can be a powerful tool in creating "self-healing" infrastructure, detecting and diagnosing anomalies, and improving situational awareness for operators to respond to various events. The following Table 3 lays out a framework of how different kinds of ML frameworks can plug into various grid resilience functions.

Table 3. Grid Resilience AI-Enabled Top Use Cases

Function	Title	Description
Natural Language Processing (Text Q&A)	Operator/dispatcher decision making support	Use AI to analyze the current situation against standard operating procedures and guidelines. By understanding the context and parameters of the situation, AI can identify the most relevant procedures and checklists, ensuring that operators follow the best practices tailored to the current conditions. AI can also simulate various scenarios and predict their outcomes, helping decision makers choose the most effective strategies for disaster mitigation.
	Correlating real-time actionable choices against SCADA alarms	By correlating real-time data, network models, and Supervisory Control and Data Acquisition (SCADA) alarms, AI can identify and localize faults faster and more accurately than human operators.
	Assist T&D Black start coordination	Following a significant power outage, the process of restoring electricity begins with generation and moves through transmission to distribution, known as black start. With grid-forming technology, the distribution network can initiate grid operations independently and expand them. AI enhances the efficiency of communication and coordination among all entities involved in the black-start process, such as transmission and distribution utilities, emergency services, and government bodies. By analyzing and disseminating information in real time, AI ensures that every participant is well informed and collaborates seamlessly.
Vision (Image pattern recognition)	Semantic weather & outage map	AI systems can more quickly identify and localize outages, automatically notify affected customers, and provide real-time updates on repair progress. This improves communication and reduces frustration during service interruptions.
	Optimal dispatcher location for storm restoration	By predicting the impact of outages and optimizing the dispatch of repair crews, AI can help utilities restore power more efficiently.
	Predictive asset maintenance	By continuously monitoring equipment conditions through sensors and data analytics, AI can predict failures before they occur, scheduling maintenance more efficiently.
Inference (Cause/Effect, Forecasting & Gap filling)	State estimation with missing measurement	In environments with sparse data, human operators may struggle to make accurate assessments. AI algorithms, particularly those based on machine learning, can infer the state of a system from limited measurements by leveraging historical data and probabilistic models, providing valuable insights where human analysis may be insufficient.
	Anomaly detection	An anomaly represents a deviation from the norm, manifesting as a significant shift outside the expected range, or as outliers. Although identifying anomalies is straightforward in theory, the sheer volume of assets to monitor makes AI the preferred solution for ongoing detection and analysis
	Uncertainty quantification	In the power industry, uncertainty quantification refers to the process of systematically and quantitatively determining the uncertainty in model predictions due to variability in input parameters, model structure, and scenarios.

2.4.1 Self-healing Infrastructure for Reliability and Resilience

Self-healing capabilities would allow the grid to autonomously identify and fix problems, minimizing the need for human intervention. Examples of what AI-enabled self-healing capabilities could look like include assisting operators with local decision making and identifying and localizing faults based on SCADA streams and quickly identifying and mapping distributed outages. Given the potential for service interruptions due to the deterioration of lines, towers, or equipment, grid operators have implemented redundant communication networks, mesh power networks, special protection schemes, and emergency procedures to prepare for such events. Traditionally, these preparations have focused on physical assets—such as the power lines or generators—with engineers determining the impact of line overloads or the network reconfiguration in case of a generator failure. Due to the computational complexity of monitoring the large scale of assets—e.g., the Western Interconnection has more than 50,000 assets—preparations and analyses for "what-if" contingency events are limited to a single potential outage from the normal state, or an N-1 contingency assessed every 5 minutes.[49] Extreme weather events like hurricanes, however, can simultaneously disrupt multiple transmission towers along their path, resulting in multiple contingencies (N-k) within a single incident. Resolving these types of contingencies within 5 minutes is very challenging for the current software capabilities. The DOE's Office of Electricity's (OE)[50] is developing AI models with the potential to address this challenge by improving power flow optimization.

2.4.2 Detection and Diagnosis of Anomalous Events

DOE OE has been working to improve event detection and wide area situational awareness using sensors across the distribution and power system through research partnerships between universities, industry, and the National Laboratories. Phasor measurement units (PMUs) have been deployed at over 2,500 locations across the nation's bulk power systems. Due to these PMU measurements, grid owners and operators now possess unprecedented quantities of data detailing the condition of the grid. AI has the potential to help improve event detection through pairing utility event records with PMU data.[51]

2.4.3 AI-enabled Situational Awareness and Actions for Resilience

Grid disruptions are inevitable, whether due to natural disasters or cyberattacks. They require preparedness, not only precaution. During the disruptions, satellite images, live-streaming data, or weather data along with operational data are critical to evaluating the situation in a control room. AI can offer a solution by identifying operational deviations or anomalies, identifying the best route to restoration, and coordinating and facilitating system self-restoration to a previously normal state. Further, employing digital twins allows for the preemptive setup of predictive operational simulations in anticipation of disruptions. Digital twins serve as digital replicas of physical grid assets, enabling proactive and risk-free simulations and analyses. Together, AI and digital twins emerge as innovative tools for enhancing situational awareness among operators, both during and following disruptive events.

In support of these grid-enhancing smart technologies, DOE's OE announced a $7 million funding opportunity announcement (FOA)[52] to enhance the electric power systems' reliability and resilience via grid-enhancing data analytics demonstrations for operations, monitoring, and control. The goal of this FOA is to demonstrate data analytics techniques, including AI and ML, with real power system data sets to improve grid resilience and reliability.

2.4.4 Resilience with Distributed Energy Resources

The increasing integration of distributed energy resources (DERs) and the expanded role of consumers and their aggregators, as a result of the Federal Energy Regulatory Commission (FERC) Order 2222: Participation of Distributed Energy Resource Aggregations in Markets Operated by Regional Transmission Organizations and Independent System Operators, have introduced increased participation and potentially more complexity into the power grid.[53] Historically, discussions on grid resilience have primarily focused on one-directional power flow, emphasizing generation and transmission; however, with the increasing integration of DERs, the conversation on resilience now needs to include both DERs and consumers who contribute to bidirectional power flow and price-sensitive demand behavior. This shift takes improved coordination between transmission and distribution (T&D) systems and DERs, which, in turn, can significantly enhance grid resilience.

AI emerges as an essential tool for facilitating this coordination and collaboration. AI's capability for orchestrating complex systems can streamline the integration of T&D with DERs, propelling grid resilience forward. AI orchestration refers to the strategic coordination and management of various AI models and power system tools, and it processes to optimize their performance and effectiveness in achieving complex tasks or objectives. This concept goes beyond the deployment of individual AI applications to embrace the integration and synchronization of multiple AI systems and their interactions with human workflows, data sources, and other technologies. Consequently, R&D efforts should prioritize AI orchestration within this context, recognizing its potential to fast-track improvements in grid resilience and adaptability. For AI orchestration, telecommunication paths, protocols to interact with, workflows of what and how to orchestrate, and reinforcement learning from human feedback should be evaluated.

2.4.5 Challenges, Accelerating Development, and R&D Needs

Achieving grid resilience requires integrating a multitude of data sources, including SCADA systems, phasor measurement units, advanced metering infrastructure, fault detection recorders, historical operational data, forecasted operational data, weather conditions, live video streams from substations, and intelligence on potential cyberattacks. There exists the need for further data sharing practices for trusted researchers and entities here as in other parts of grid operation and security. Developing new standards for interpretability and benchmarking of AI models for grid resilience is also necessary, given the unique constraints and importance of power grid resilience. In addition, ensuring models do not leak critical infrastructure information and developing secure model training tools e.g. federated learning, is another key area of R&D for algorithmic development.

2.5 Grid Resilience in the Face of Increased Climate Risks

Grid resilience challenges will increase from exposure to more extreme weather events, driven by long-term trends from climate change. The average number of severe weather or climate events per year has more than doubled over the last five years, compared to the 1980-2022 average.[54] Understanding the impacts of a changing climate requires a systematic modelling approach to climate systems and a fine-grained understanding of power grid infrastructure. AI can help tackle this complexity and characterize extreme weather hazards on infrastructure, enable real-time monitoring of climate events, and enhance longer term grid planning to insure against climate risks.

2.5.1 Characterization of Extreme Weather Hazards on Electricity System Infrastructure

The ability to predict and respond to power grid outages caused by adverse climate and weather events is key to ensuring the reliability and resilience of the grid. The Climate Mapping for Resilience and Adaptation (CMRA) assessment tool integrates information from across the Federal government to provide valuable insights and data regarding location-specific exposure to climate-related hazards.[55] Resources like the CMRA help reduce the difficulty of predicting extreme weather events and provide valuable data outputs, but large variances in the environmental and weather conditions experienced across the scope of the grid still make it difficult to determine how and when these events will likely lead to significant outages. AI, advanced statistics, and ML tools present an opportunity for the utilization of large sets of weather variables and outputs from resources like CMRA to predict power system outages. Where existing model-based studies are often limited in geographic scope and have significant operational constraints, AI tools can enable improved accuracy, specificity, and flexibility. As the impact and frequency of extreme weather events increase, the AI-enabled capability to accurately predict outages and assess their severity over the entirety of the grid would transform the ability of grid planners and operators to make decisions that maximize resiliency.

2.5.2 AI-enabled Monitoring and Detection for Climate Risks

Grids can be enhanced with the integration of sensors, data analytics, energy storage systems, energy management systems (EMS), advanced distribution management system (ADMS), and various energy technologies to evolve into “smart” grids. These smart grids can achieve higher efficiency levels when AI is used to predict or identify climate-related anomalies, such as wildfires, floods, heatwaves, polar vortexes, and droughts. For instance, AI is already being deployed to detect wildfire activity through satellite imagery, drone inspections of smoke, and sensor data like temperature or humidity. AI’s role extends beyond detection to prevention, especially in avoiding wildfires sparked by electrical equipment, by forecasting the likelihood of wildfires and deploying sensors where AI has identified optimal locations of electrical poles. With the addition of more sensors, optimal sensor placement, utility private cloud environments for raw image data storage, and advanced telecommunication technologies such as 5G/6G, AI weather-power grid models can quickly process and relay alerts from raw video footage to nearby substations. This enables the mitigation of wildfire risks through the strategic isolation of affected areas and the rerouting of power, thereby reducing the impact on power supply disruptions. Additionally, AI models can identify vulnerabilities in the power grid by simulating how extreme weather events, driven by climate change, affect grid stability and infrastructure. This allows for proactive grid strengthening and the development of strategies to enhance resilience against climate-induced disruptions.

2.5.3 Grid Planning for Climate Impact

Historically, for fossil fuel-based resource adequacy planning, exploration of climate impacts on the electricity system have been very limited. Until now, resource adequacy assessments have been conducted seasonally or annually by planning engineers through offline production cost model simulations, which are based on user-defined planning scenarios, direct current power flow models, and long-term weather and demand forecasts.[56] This approach to determining the peak demand has been working for many decades because the load/demand curve is almost identical from year to year and season to season. But increasing climate risks shift the models needed to account for extreme weather events driven by climate change. Extreme cold and heat can cause traditional thermal generation to fail or underperform. Similarly, the transition to weather-dependent renewable energy—such as hydropower dams, solar, or wind — introduces similar sensitivities for grid planner to account for. Extreme weather events also impact demand-side modelling, which can introduce acute shortages from a “perfect storm” of spiking demand and underperforming generation across the board for grid operators to handle. Understanding the shifting probabilistic nature of these events will require new climate modelling methods and tighter integration between grid planners and such models.

AI can bridge the gap between global climate models, which operate on a vast scale, and the localized needs of power system planning and operations. For example, AI can be used to downscale global climate models to generate high-resolution weather forecasts and climate projections, such as predicting temperature changes, precipitation patterns, and extreme weather events that are specific to local regions. By analyzing historical data alongside climate projections, AI algorithms can suggest future energy demand and supply fluctuations due to climate change. This predictive capability helps system operators plan for resource adequacy. Bridging the gap could provide valuable insights for making energy systems more resilient and efficient in the face of changing climate conditions. Additionally, AI models can identify vulnerabilities in the power grid by simulating how extreme weather events, driven by climate change, affect grid stability and infrastructure. This allows for proactive grid strengthening and the development of strategies to enhance resilience against climate-induced disruptions.

2.5.4 Challenges, Accelerating Development and R&D Needs

As mentioned, data and modeling present a significant challenge for researchers in the power grid domain, a complexity that is further worsened by the evolving dynamics of climate change. Bridging the gap between the wealth of industry data that exists and the limited ability of the research community to access it remains a difficult task. A promising strategy to accelerate data sharing involves the acceptance of synthetic data by the industry, validated through the comparison of actual and synthetic power flows. AI can play a crucial role in this process, fine-tuning the alignment between real and synthetic datasets by adjusting input parameters.

AI is able to generate novel datasets, scenarios, or surrogate models tailored to the nuances of climate change. In scenarios featuring extreme weather, combined with identified power flow patterns, AI orchestration can effectively coordinate with power system tools—such as product cost models or power flow analyses—to craft a generic framework capable of incorporating phenomena such as polar vortexes, long droughts, or heat waves. This orchestration approach not only enhances our understanding and management of the grid in the face of climate change but also paves the way for more reliable and resilient power systems.

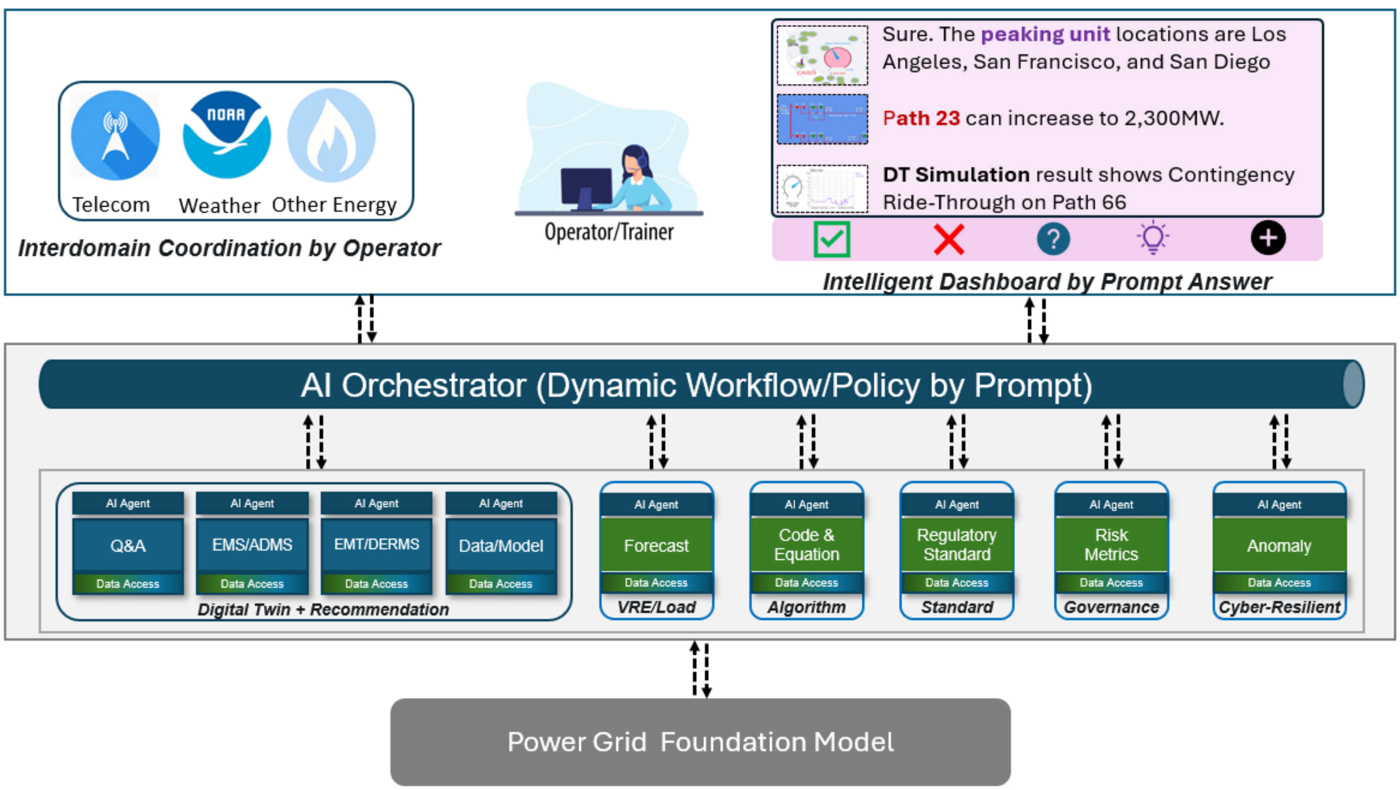

Figure 3. AI Orchestration for Power Grid

2.6 Security and AI-Specific Risks

Given the critical importance of the grid, it is important to consider a broad range of potential risks, including security and AI-specific risks, that could be posed by the deployment of AI alongside the electric system. The risks to energy infrastructure from AI can be broken down into four basic categories:

1. Unintentional Failure Modes of AI
2. Adversarial Attacks Against AI
3. Hostile Applications of AI
4. Compromise of the AI Software Supply Chain.

As a still nascent and evolving technology, the understanding of the security risks of AI will continue to evolve. However, as adoption of mature AI continues to diffuse across the energy industry, professionals in the sector need a working understanding of both the inherent and potential risks of AI.

2.6.1 Risk Category 1: Unintentional Failure Modes of AI

This category refers to AI created for beneficial purposes, but which is unintentionally misused or has unintentional failures, leading to negative outcomes. A non-exhaustive list of unintentional failure modes is provided here:

- **Bias** in AI is the systematic shift of a decision-making process away from its goal, usually due to a mismatch between training data and real-world use. Bias in AI systems is discussed further in Section 4.2.
- **Extrapolation** is the use of a model to make predictions about "unexpected" events – situations outside that model's experience –which can lead to unpredictable behavior.
- **Misalignment** is when an AI model's behavior deviates from the goals of its designers, typically due to poorly aligned training data or poorly defined objectives.

Across all these failure modes, it is difficult to eliminate the risk entirely, but the problems can often be acceptably mitigated through the application of best practices and/or further research into mitigations. Further R&D of domain-aware AI can help address these risks. Minimizing these risks is critical when considering the adoption of AI for various energy system applications, given the critical nature of the grid and the low tolerance for failure.

2.6.2 Risk Category 2: Adversarial Attacks Against AI

Machine learning AI systems are susceptible to a variety of novel vulnerabilities, in addition to traditional cybersecurity vulnerabilities. These vulnerabilities can be exploited by an adversarial attack – which occurs when AI designed and deployed for beneficial purposes is intentionally manipulated by adversaries, to create negative outcomes. Adversarial attacks are distinct from traditional energy system cybersecurity risks – often exploiting the data-driven nature of AI methods – and vary by objective, access requirements, and knowledge requirements. Common types of attacks include the following:

- **Poisoning attacks** add, modify, or alter the data used to train an artificial intelligence model, in order to force the model to learn the wrong behavior.
- **Evasion attacks** generate adversarial input data that may look indistinguishable from regular data to a human but leads to a desired model output, typically counter to the wishes of the model creator.
- **Data extraction attacks** seek to leak information from a machine learning pipeline.

Adversarial attacks against AI, and defense against them, is an active area of research and is distinct from traditional cybersecurity. Even so, data and model security remain critical considerations for guarding against adversarial attacks against deployed AI systems. While measures such as careful curation of training data, tailored access controls, and human supervision can help mitigate the risk of adversarial attacks, current detection and defense techniques are not yet mature enough to guarantee security against sophisticated attacks. Further research in this area is still needed, particularly as AI adoption continues across the energy system.[57]

2.6.3 Risk Category 3: Hostile Applications of AI

AI can be created and used by adversaries to plan or execute cyber or physical attacks on energy infrastructure. In some cases, AI may lower the difficulty of an attack, enabling less-sophisticated adversaries to carry it out. In others, the use of AI may still require sophistication, but could enable more effective attacks than were previously possible. A non-exhaustive list of ways in which adversaries might use AI for hostile means includes:

- Automatic parsing of written text for vulnerability insights.
- Model inference or model completion based on available data.
- Model-based design of attacks.
- Autonomous control of devices for physical attacks.
- Autonomous malware.
- Evasion of cyberattack detection measures.

An analysis of publicly available energy information should be performed to assess what sensitive information may be inferable with AI methods. If that analysis identifies sensitive information is potentially inferable, additional steps may be needed to mitigate risks. The deployment of AI-aware cybersecurity solutions, as well as further tracking of hostile applications of AI can assist energy system operators in hardening digital infrastructure against potentially AI-enabled cyber-attacks.

2.6.4 Risk Category 4: Compromise of the AI Software Supply Chain

Unlike Risk Category 2, this category is not focused on the manipulation of the AI models themselves, but rather analyzes the ways in which AI software supply chains might face traditional cybersecurity risks – such as those common to many digital systems currently used in energy system operations. As AI is software, it is subject to the same cybersecurity risks of other software.

An adversary may exploit AI software not only to attack the AI system, but as an intrusion vector to a victim's broader energy infrastructure systems. This can occur through both proprietary and open-source software, which AI systems are heavily reliant on – and is potentially a particular concern as AI tools, particularly those relying on generative AI techniques, shift from bespoke design to relying on common tools, libraries, and in some cases, foundation models. As such, cybersecurity and energy system supply chain security best practices are critical to securing the AI software supply chain.

In support of a broader understanding of software supply chain challenges in energy infrastructure, DOE's Office of Cybersecurity, Energy Security, and Emergency Response (CESER) released a report in 2022 examining cybersecurity threats, vulnerabilities, and risks to supply chains for digital components in energy sector systems.[58]

2.6.5 Challenges, Accelerating Development and R&D Needs

Future work on AI risks to energy infrastructure should include a more rigorous analysis of the risks identified here that quantifies the consequence and difficulty factors of risk and is informed by threat assessments. In addition, a more in-depth analyses of the application classes, including identifying AI approaches relevant to each application class and most likely sources of risk, would be of value. Best practices should be developed to help guide practitioners and downstream users of AI. However, several important knowledge and methodology gaps remain. This report identifies a number of research topics for which greater research funding would lead to significant improvements in the ability of the critical energy infrastructure sector to use AI safely. DOE will also be conducting an annual assessment of AI risks to critical energy infrastructure in accordance with Executive Order 14110.

3. AI to Advance a Clean Energy Economy

Building the clean energy economy will fundamentally transform sectors like transportation, buildings, industrials and manufacturing, and agriculture. It will also drive innovation in new, cross-cutting sectors such as the burgeoning hydrogen economy, critical materials, and geologic mapping. As a powerful new capability, AI can help support the needed transformative technologies across these diverse sectors and aid the United States in meeting its goals of cutting emissions in half by 2030 and achieving net-zero emissions economy-wide by 2050, as well as furthering our energy security and economic competitiveness. This section highlights example opportunities for AI to accelerate progress across the clean energy economy.

The transportation sector, which includes light, medium, and heavy-duty vehicles, is currently the largest source of GHG emissions in the United States, responsible for 29% of total GHG emissions.[59] Deploying the charging infrastructure needed to support EVs on the road will require significant public investment and special consideration for how these new loads interact with the power grid. Designing and manufacturing EVs that meet the range and price requirements of users will require continued R&D in new materials, batteries, and optimized industrial manufacturing processes. AI can help mitigate these issues through planning and optimizing charging station location, intelligent vehicle-to-vehicle communications, and charge sharing. AI-driven research can also accelerate the development of more affordable and efficient battery technologies.

The industrial sector accounts for approximately 23% of total GHG emissions in the United States and faces challenges in decarbonization that include high energy consumption in the manufacturing processes, reliance on fossil fuels, and significant waste generation.[60] For example, cement and steel production are both carbon and energy intensive due to high temperatures and the chemical reactions required, leading to significant CO_2 emissions. AI can help address these issues in the industrial sector by optimizing manufacturing workflows, creating a more circular and sustainable supply chain while improving supply chain logistics, enhancing material efficiency, and facilitating adoption of on-site renewable generation and integration of electrification in manufacturing processes.

The residential and commercial building sectors, which account for 13% of total GHG emissions in the United States (and increase to 30% when emissions from electricity consumption are allocated to these sectors), face challenges with the high costs of retrofitting, complexities of integrating renewables, and the need for widespread adoption of energy-efficient practices.[61] AI can play a role in reducing the sector's emissions by enabling building management systems to dynamically optimize energy consumption through real-time control of HVAC and lighting, based on weather and occupancy data. AI can also support predictive maintenance for energy systems efficiency and design new building materials and structural designs.

The agricultural sector is responsible for approximately 10% of total GHG emissions in the United States but plays a key role in ensuring our food security and in supporting local economies.[62] At the same time, as a fundamentally land-oriented industry, agriculture is often the first industry to encounter large-scale renewable energy deployment. AI can help optimize the co-integration of agriculture and renewable energy – a nascent practice known as "agrivoltaics." The bioeconomy is also intricately linked with agriculture – here AI can also help accelerate R&D around biomanufacturing and bioenergy. Finally, AI can also help drive continued efficiencies and productivity gains through precision agriculture that aids in managing farming practices more efficiently, helping reduce emissions and continuing the economic competitiveness of the US agriculture industry.

To realize our climate goals will require innovation and deployment in new cross-cutting sectors, such as the hydrogen and carbon dioxide storage industries, geologic mapping, methane mitigation, and critical minerals and materials. AI can play an important role in optimizing infrastructure for new hydrogen and carbon dioxide storage industries, unlocking insights for subsurface characterization and mitigating methane leaks, and material discovery to mitigate supply chain challenges for critical materials and ensure continued clean energy materials innovation. The DOE Office of Science funds a variety of research efforts in materials discovery, including into critical materials, through their Basic Energy Sciences (BES) program, with broad applications in these sectors.[63]

3.1 Transportation

Transportation is a key sector of our economy, facilitating the movement of people and goods. It is consequently also a significant portion of our emissions. The year-over-year growth of EV adoption requires a similarly aggressive buildout of associated charging infrastructure. The deployment of these load centers also poses challenges for grid operators facing distributed load growth. In this section, we non-exhaustively highlight how AI can tackle these challenges for the decarbonization of the transportation sector, with further discussion on how AI can assist car manufacturers with new designs in Section 3.3 and discover new battery chemistries in Section 3.5.1.2.

3.1.1 Planning for EV Charging Networks

AI can be used to optimize a public and private EV charging network by analyzing historical data on EV usage, including peak times and locations of high demand, to predict future charging needs and help meet expected demand efficiently. It can also be used in the site selection process by processing geographical data, infrastructure data, need, and traffic patterns to identify optimal locations for installing charging stations. It can ensure that stations are accessible and convenient for EV drivers, while considering existing grid capacity and future load growth.

Since public EV chargers are self-service, operations and maintenance play a vital role. AI can monitor the health and status of charging stations real-time, communicating uptime and downtime status of a charger, and predicting maintenance needs before they become critical. This will aid in high reliability and availability of the charging network.

For public and private fleets and their associated charging depots, the routes and usage are more predictable. AI can provide fleet optimization and manage the charging of a fleet; this includes factoring in a vehicle's schedule and optimizing charging times based on the route and usage patterns. It can also be used to manage electricity consumption more aggressively to align with off-peak charging rates, where fleet charging can be scheduled during low-demand periods to reduce their costs. AI can also provide fleet operators with higher incentives to consider integrating renewable generation sources or energy storage into their charging depot, because it can manage and optimize integration of these onsite renewables with charging infrastructure, providing higher cost savings and a much cleaner source of charging that places less burden on the grid.

3.1.2 Vehicle-Grid Integration and Vehicle-to-Vehicle Interfaces

Managing the vehicle-grid interface is critical. AI can help enable multiple vehicle-grid integration (VGI) approaches. AI can help balance the load on the grid by predicting peak charging times and managing the supply of electricity, which will help prevent overloads and ensure that the grid can support additional demand from EVs. AI can also be used for smart charging solutions, making charging more efficient by optimizing charging schedules based on the grid's demand patterns, electricity prices, user preference, and battery health, and recommending when to charge the vehicle based on these factors. This reduces strain on the grid and can also lower charging costs for businesses and consumers. AI can also forecast peak load times and adjust charging rates dynamically, balancing charging needs with grid capacity. It can also stabilize the grid by controlling the charging and discharging of batteries and provide ancillary services like frequency control and load balancing. In emergency situations, AI can enhance the grid systems and provide critical support to the grid during sudden spikes in demand or unexpected power outages by identifying and mobilizing available EVs in a bidirectional vehicle-to-grid network that can supply energy back to the grid. This rapid response is crucial during emergencies, such as natural disasters or grid failures.

Vehicle-to-Vehicle (V2V) communications can also be enhanced with AI. AI-enabled V2V communication can allow EVs to share information about their battery levels and anticipated charging needs, which can lead to cooperative decision-making regarding charging station visits, helping to distribute charging load more evenly across the network and reduce peak demand. In a V2V network, AI can enable smart energy exchange between vehicles, allowing for transfer of battery power from EVs with surplus energy to those in need, which is useful for backup and emergency situations to balance energy within a fleet of EVs or promoting efficient use of stored electricity.

3.2 Buildings

Decarbonizing buildings and creating new paradigms for how buildings interface with the power grid will be critical for meeting 2035 clean electricity goals and achieving a net-zero carbon economy by 2050. The increased deployment of Internet of Things (IoT) is enabling a vast deluge of data about buildings, which can be leveraged by AI to optimize energy performance and building comfort and provide cost-savings to building operators. At the same time, electrification of building appliances and integration of distributed energy systems like rooftop solar and electric vehicle chargers, are increasing the importance of load-flexible, grid-interactive buildings in maintaining a resilient power grid. AI can help realize the potential cost savings as well as monetize the value-add role of building for our power grid, while addressing the increasing complexity faced by building operators.

3.2.1 HVAC Optimization

AI-based methods and ML techniques are expected to help buildings run more efficiently and provide greater comfort levels to occupants. Buildings and HVAC systems have historically been designed, built, and programmed as fixed systems and with static environmental assumptions. This can lead to inefficiencies as building use, occupancy, and environmental factors change. AI can be applied to parse data collected by building systems and integrate with controls to continuously adjust setpoints to optimize HVAC performance while maintaining or improving occupant comfort. AI-based methods can provide additional controls to operators and can increase the load flexibility of buildings for participation in Virtual Power Plants (VPPs).

3.2.2 Virtual Power Plants

VPPs are aggregations of distributed energy resources, such as rooftop solar with behind the meter batteries, EVs and chargers, electric water heaters, smart buildings and their controls, and flexible commercial and industrial loads that can balance electricity demand and supply and provide utility-scale and utility-grade grid services like a traditional power plant. See Section 2.4.4 for more on distributed energy resources.

With electricity demand growing for the first time in two decades, VPPs will play a key role in achieving a goal of 100% clean electricity by 2035, potentially addressing 10-20% of peak demand.[64] AI and ML can help realize the rapid deployment of VPPs by processing increasingly large datasets generated by the deployment of connected and grid-interactive devices and advanced metering infrastructure. Smart meter data can enable transitions from monthly billing to hourly or even 15-minute data resolutions. AI/ML can be used to detect loads in smart-meter data and facilitate the identification and enrollment of participants in VPP programs by providing customer segmentation. AI can also support increased engagement and participation in behavioral demand response programs – democratizing the benefits of participation in VPPs. AI/ML models can help identify and target customers and facilitate enrollment in VPP programs, improve weather and market forecasts and forecast resource availability. During operations, AI can support the coordination and dispatch of large multi-asset fleets of devices, as well as identify assets that are underperforming and may require preventive maintenance.

Data ownership is one of the key challenges stakeholders have identified, particularly when it comes to buildings. Building operators, tenants, grid operators, and VPP providers all face different incentive structures which can constrain the sharing of data and decision-making. AI can help interface between difficult to ascribe building tenant preferences and the economic structures that craft the incentives faced by owners, operators, and providers, but this often requires business models and data sharing agreements to support AI adoption. To facilitate the adoption of VPP by building operators, DOE's Building Technologies Office (BTO) convenes the Grid-Interactive Efficient Buildings (GEB) initiative to support research and stakeholder engagement for buildings to better interface with power grids.[65]

3.2.3 Embedded Energy and Construction

AI can also help decarbonize and reduce the energy demands of the construction of buildings themselves. Cement, as the primary building material used today, represents 7-8% of global carbon emissions and 1-2% of US emissions.[66] Despite its ubiquity, there is still substantial design space left for new cement formulations. AI can be used to design and optimize low-carbon cement designs, enabling accelerated materials formulation and innovation. AI can also be used to identify efficiencies in building construction. The planning and sequencing of steps for building construction is a fairly manual process and can be optimized with AI to unlock process efficiency and reduce waste at construction sites. AI can also be used for structural optimization of building designs, potentially reducing material intensity and lowering construction costs. Realizing these efficiencies and process innovations with AI to drive emissions reductions will require further digitization of the construction industry and new standard setting procedures to safely integrate AI designed solutions and methods.

3.3 Manufacturing and Industry

The manufacturing and industrials sectors are key parts of the decarbonization roadmap and in maintaining a resilient clean energy supply chain. With historic BIL and IRA provisions, DOE has played a key role in securing a domestic clean energy supply chain[67] and supporting decarbonization of the broader industrial base.[68] AI can play an important role in the manufacturing and industrials sector by enabling generative product design, automating manufacturing, characterization, and qualification, and optimizing operations. These innovations not only reduce cost and improve domestic competitiveness but lead to improved material efficiencies and reduce embodied emissions across the economy.

3.3.1 Generative Design Factors for New Structural Materials

The advent of new manufacturing techniques, such as additive manufacturing and composite materials, has led to an explosion in the design space for structural materials and die tooling. Generative AI can allow for the evolution of design structures to take advantage of novel manufacturing techniques, while reducing material intensity, input cost, and scrap waste. For instance, DOE's Advanced Materials and Manufacturing Technology Office (AMMTO) has funded research to support the automotive sector use of AI-designed lightweighted structural components which use less material, lead to lighter components, and higher fuel efficiencies.[69]

3.3.2 Component Manufacturing, Characterization, and Qualification

In addition to design, AI can also play an important role in the factory line. Computer vision models can be deployed to perform automated visual quality control. AI models can also enable the use of advanced characterization tools and use data-driven learning to extract complex quality control signals. DOE AMMTO, in partnership with the Clean Energy Smart Manufacturing Innovation Institute (CESMII), is supporting manufacturers to adopt these digital technologies and AI in manufacturing.[70]

Computer vision models can also be applied during the component fabrication process to assess internal stresses and quantify the difference between component design and as-built conditions. The goal of leveraging AI models in this way is to move toward a "born-qualified" component development process which will reduce the time between building a part and utilizing it as part of an assembly or end product. DOE's Office of Nuclear Energy (NE) is undertaking efforts to examine additively manufactured parts in real-time to calculate internal stress concentration and microstructure to predict component performance.[71]

3.3.3 Optimized Operations and Predictive Maintenance

Similar to how AI can be used for predictive maintenance of grid assets (as discussed in Section 2.3.2), AI can also be utilized to improve operations and maintenance (O&M) for deployed clean energy technologies or for capital equipment used in manufacturing and energy technologies. In factories, AI can be coupled with cheap IoT sensors to perform predictive maintenance, reducing downtime of different capital equipment. For certain primary and recycled feedstocks, computer vision can be utilized to sort out material inputs more efficiently and improve operating efficiencies.[72]

3.4 Agriculture

Agriculture is the foundation for food security and plays an important role in many local economies. As a primary land use, it is often the first to encounter utility-scale renewable development. AI can play a mediating role by optimizing the colocation of agriculture and renewable generation. In addition, AI also plays a key role in enabling the bioeconomy and biomanufacturing, as well as supporting increased agricultural productivity through precision agriculture, which also serves to reduce emission intensity of food production.

3.4.1 Land Use for Utility-Scale Renewables

Optimizing siting of utility-scale renewables (and transmission lines) integrated within broader land-use planning presents a complex, multi-objective problem. Siting solutions will need to be found that satisfy the priorities of affected communities as well as the direct landowners. One promising solution is co-location of renewable energy with existing land uses, improving land-use efficiency. One specific example of such co-location is agrivoltaics, the combination of solar and agriculture, but other examples may include co-location with wind or geothermal or the use of agriculture for biofuels. DOE is already supporting investments in this space. For example, NREL's Made in America Solar Challenge awarded finalists building AI and software solutions to optimize agrivoltaics.[73] AI can also translate land use challenges, from siting, permitting, and optimizing how to incorporate other economic uses, into opportunity maps for renewable energy developers. Solving this challenge will be critical to enabling a 100% clean electricity system. Land access concerns can delay or limit projects, possibly forcing projects into less cost-effective areas and preventing local generation from being deployed with concomitant resilience benefits.

3.4.2 Bioenergy

The integration of AI/ML with automated experimentation, genomics, biosystems design, and bioprocessing technologies is poised to revolutionize bioenergy research. To identify the opportunities and challenges in this emerging research area, DOE Office of Science's Biological and Environmental Research program (BER) and the Bioenergy Technologies Office (BETO) held a joint virtual workshop on AI/ML for Bioenergy Research (AMBER) in August 2022 and published a workshop report in April 2023.[74] Areas of particular interest for future directions from the workshop were building microbes and microbial communities to specifications, developing closed-loop autonomous design and control for biosystems design, and advancing scale-up and automation.

DOE currently leads state of the art efforts in AI/ML for bioenergy in both applied and fundamental R&D. The BETO-funded Agile Biofoundry and Advanced Biofuels and Bioproducts Process Development Unit (ABPDU) use a variety of AI/ML techniques for engineering biology. These DOE funded capabilities partner with companies in the space to ensure these state-of-the-art approaches are speeding time to market adoption for bioenergy-related technologies. On the fundamental side, BER seeks to develop AI/ML techniques in association with lab automation to accelerate discovery research and explore innovative possibilities for the design of biological systems for beneficial purposes. These efforts are being pursued within BER's Genomic Science programs, the Bioenergy Research Centers as well as the Joint Genome Institute (JGI).

3.4.3 Precision Agriculture

The deployment of cheap field sensors and mass availability of high-quality satellite imagery are enabling advances in precision agriculture, where models can extract insights about the state of health of different subfields and optimize the delivery of fertilizer and water to each individual plot. The DOE's Idaho National Laboratory has developed CropAIQ, a deep-learning based tool for farmers to estimate crop yields from satellite imagery.[75] ARPA-E has also funded additional development of cheap, biodegradable sensors to further precision agriculture data gathering.[76] Precision agriculture can enable greater resource efficiency in agriculture, improve productivity, and reduce emissions, securing food, climate, and energy security.

3.5 Cross-Cutting Technologies

While AI can help tackle key bottlenecks to decarbonization across the major economy sectors, AI can also play an important role in supporting cross-cutting issues upstream of traditional economic sectors, which could in turn impact load growth, energy storage, and renewables adoption. In this section, we outline specific opportunities for AI to support recovering critical materials and discovering new materials, hydrogen and carbon dioxide transport solutions, mitigating methane leaks, and better understanding the subsurface. AI-driven acceleration in these upstream and cross-cutting technologies will also be key in building a clean energy economy to meet climate goals.

3.5.1 Critical Materials Recovery and Material Discovery

With the need for critical materials growing rapidly, and a concern about security and resilience of future critical mineral and material (CMM) supply chains, AI holds the potential to help the United States and our allies meet this need by diversifying and expanding supply, developing alternatives, and improving the efficiency of new CMM technology. AI could play key roles in locating new minerals and accelerating their recovery from conventional feedstock. Incorporating AI into the processing, refining, and recycling of CMM can help reduce costs, resource needs, and environmental impacts and can support the competitiveness of the United States.

In addition to accelerating the domestic supply of critical materials, AI can also be utilized to identify novel high-performance materials through accelerated computational screening and automated discovery of new materials. These materials can assist with improving material intensity or create new pathways for material substitution altogether and alleviate United States supply chain constraints for critical materials. [*See Inset "Spotlight: Pacific Northwest National Laboratory"*][77]

Spotlight: Pacific Northwest National Laboratory

Scientists from the Pacific Northwest National Laboratory, in collaboration with Microsoft, used AI to accelerate the time to discovery for new battery materials. Using AI, 32 million potential materials were narrowed down to 18 in just 80 hours – with scientists synthesizing a material that can reduce lithium usage in batteries by up to 70%. This work demonstrates how advanced AI models can be leveraged to facilitate the discovery of new battery materials.

3.5.1.1 Critical Materials from Waste Streams

Secondary feedstocks that include byproducts and waste materials, such as coal ash, acid mine drainage, bauxite residue, mine tailings, and produced water, have the potential to provide significant market share of a variety of critical minerals and materials, but make up almost none of the market today. Faster and more accurate characterization of the potential resource using AI can improve the prospects for these resources to come online in the near term, especially through combining information from geologic sources and company records related to the generation of the waste streams. E-waste is another area where AI and ML techniques can help improve performance and lower costs. AI/ML, coupled with continuous monitoring, will help to perform real-time evaluation of extracted materials, and enable real-time adjustments of critical material processing technologies. Using AI to find ways to turn waste streams into economic resources can contribute towards developing a circular economy and has the potential to aid communities that have had environmental justice concerns related to waste by having more monitoring, reducing the need to extract virgin materials, lowering the environmental impact, and providing possible economic opportunities.

3.5.1.2 New Material Discovery

Enabling the discovery of new, high-performance, materials such as solar active materials, battery chemistries, carbon capture sorbents, hydrogen catalysts, and other materials for clean energy industries will ensure American leadership in the next generation of clean energy technology. AI can also help mitigate shortfalls in critical minerals and materials by identifying substitutionary materials with similar performance. The Basic Energy Sciences program within the DOE Office of Science supports the fundamental scientific research necessary to realize new materials for clean energy applications, including the development of new approaches to predict, synthesize, and characterize materials that leverage novel AI and automation technologies. While traditional numerical models, such as Density Functional Theory and Molecular Dynamics can often be helpful tools for modelling various material classes, they are often too computationally intensive. Data-driven AI can act as surrogate models and perform accelerated computational modelling, to enable high-throughput screening and discovery of new material families. For applications of AI for materials discovery and design specific to hydrogen, refer to 3.5.2.1.

AI, when coupled with robotic automation, can also enable high-throughput experimental synthesis and characterization of new materials. Several research groups have already utilized robot arms and automation to explore vast material design spaces by using AI to intelligently design experiments. Several of these "self-driving labs" have been funded at various universities and national labs and have contributed to discoveries of improved catalysts,[78] 3D-printed composites,[79] and quantum dots.[80]

Finally, large language models can parse vast amounts of scientific literature to highlight material trends and infer material properties before they are measured. While such tools are already becoming prominent in the biological sciences, large language models can be used to understand chemical compound properties and material properties as they emerge from literature, helping accelerate the pace of clean energy materials discovery. These models can also be helpful for summarizing research fields concisely for new researchers.

3.5.1.3 Nuclear Fuel Materials

The R&D of nuclear fuel materials typically requires complex fabrication logistics, followed by long irradiation qualification campaigns to determine fuel performance, accident tolerance and post-irradiation durability. These activities can be significantly accelerated, and the amount of waste material produced can be significantly reduced through the utilization of AI-assisted material selection. There already exists a large set of nuclear fuel development and testing data which can be utilized to train a foundational model. Additionally, if the utilization of AI could significantly reduce the time, and funding burden for nuclear fuels qualification, broader investigations of fuel compositions and form factors would be possible, allowing researchers to expand the scope of investigations, which may lead to novel fuel types with unique safety and efficiency characteristics.

3.5.2 Hydrogen and Carbon Dioxide Industry

Achieving the goal of a net-zero carbon economy in the US by 2050 will require developing infrastructure to safely transport vast quantities of CO_2 captured at point sources or directly from the air and H2 generated from renewable energy sources. DOE's Hydrogen Shot™ aims to support the unprecedented pace and scale of technology and infrastructure by lowering the cost of clean H_2 costs 80% to $1 per kilogram within one decade while expanding the United States energy workforce.[81]

3.5.2.1 Materials Development for H2 Use Cases

AI/ML can support the Hydrogen Shot by assisting in the development of structural and functional materials. AI/ML tools could help assess the suitability, performance, life, and risks of novel structural materials for use in H_2 production, transport, and surface storage. AI algorithms that incorporate physical mechanisms could reduce uncertainty in the predicted performance of new materials and more reliably predict the life and performance of existing structural materials under specified operating conditions (including impurities). AI could potentially draw upon recorded data (e.g., maintenance or regulatory records, operational records, and environmental/in situ data) to model impacts on the life of structural materials used in the H_2 industry (including retrofits) under tracked conditions.

Novel and advanced functional materials can optimize and lower the cost of processes used in H_2 production, use, transport, and storage (e.g., metal hydrides that adsorb/desorb H_2)—and simultaneously address the degradation issues affecting structural materials. AI could help characterize a range of functional materials for H_2 use cases, including gasifiers, reformers, electrolyzers, catalysts and cathodes in fuel cells, separations membranes, and solid storage materials such as metal hydrides. AI methods could appropriately target development of new materials (including catalysts) for more efficient, low-temperature, proton conducting fuel cells and electrolyzers.

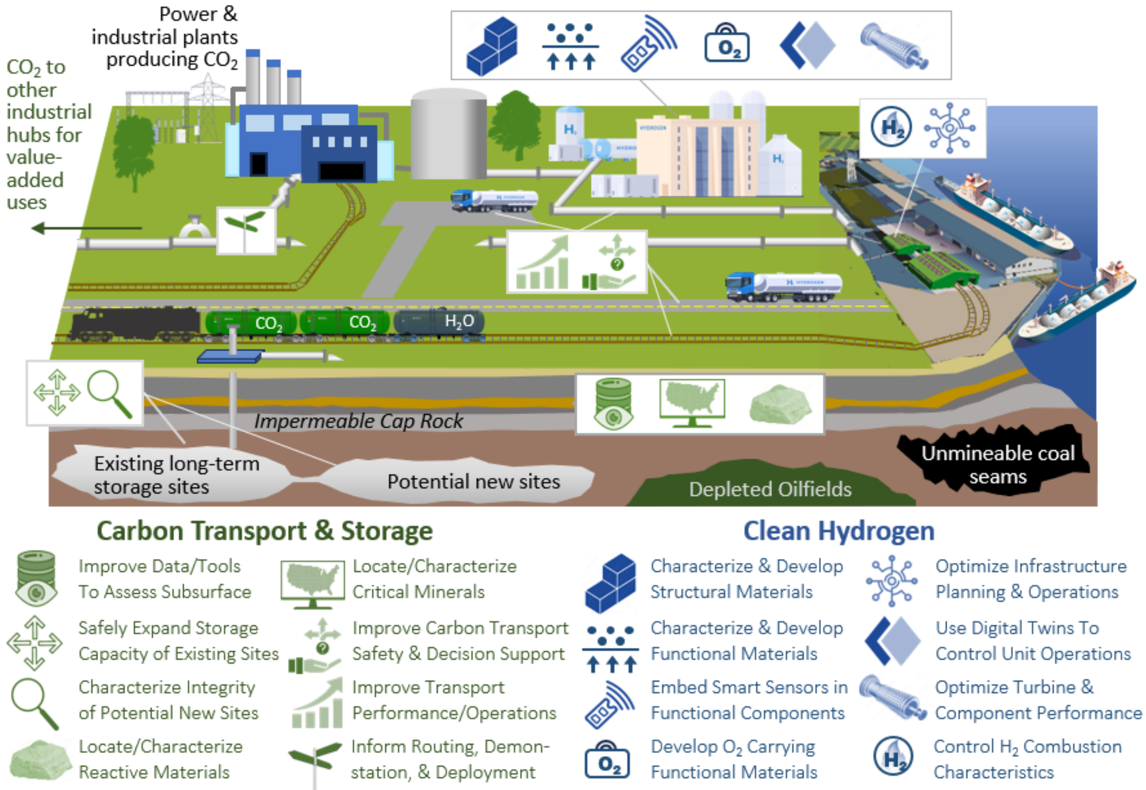

Figure 4. Roles for AI in Clean Hydrogen, Carbon Transport and Storage

3.5.2.2 Control and Optimize Unit Operations

Virtual copies of all system components and their interactions, digital twins, could help optimize H_2 and carbon management operations. Potential applications include optimizing operating parameters in turbines; characterizing, assessing, and correcting H_2 combustion processes; and characterizing variable input and output in real time to adjust gasification. To improve H_2 combustion systems, AI could identify dynamic stability limits, anticipate when the system is approaching those limits, and recommend or take corrective action. Ultimately, AI models may replace physics-based models for H_2 combustion, but hybrid models can combine the strengths of both in the interim: the real-time, data-driven responsiveness of AI/ML models (generally based on normal operating data) and the ability of physics-based models to suggest options for handling out-of-the-ordinary conditions.

3.5.2.3 Strategic Planning for CO2 Transport

To optimize CO_2 transport and lower risks, AI can help generate models that integrate a range of social equity, logistic and energy issues (including for multi-modal transport options), information on local initiatives, routing regulations, and geospatial analytics. AI/ML can rapidly parse the massive data sets collected for decades across thousands of miles of oil and gas pipelines and, more recently, mixed fluid and dedicated CO_2 pipelines, and swiftly evaluate various scenarios to help with leak detection. With such tools, AI might help develop and regularly update pipeline maintenance strategies.

Strategic CO_2 transport planning must also consider that all critical infrastructures are potentially vulnerable to climate change impacts such as hurricanes, ground subsidence, wildfires, sea-level rise, heat waves, and drought. An AI/ML model can suggest areas of greatest risk to offshore infrastructure by combining existing models for submarine landslides, extreme wind/wave/current events, etc. Challenges in developing AI tools for CO_2 transport planning include the large amount of disparate data from multiple sources that must inform any predictions or decision making, especially when drawing from data systems that don't typically interact with each other (e.g., maritime versus land topography data systems).

3.5.3 Methane Mitigation

Methane (CH_4) is a potent GHG emitted by both natural (~40%) and human sources (~60%) around the globe. Emissions at ground level can endanger and pose a hazard to individuals close to production facilities or near any rupture along a high-pressure pipeline. CH_4 also contributes to ground-level ozone, which can impair lung function and cause other serious respiratory or cardiovascular conditions.[82] Although CH_4 persists in the atmosphere for a much shorter time (~10 or 12 years) than CO_2 (300 to a thousand years), it traps about 80 times more heat (over a 20-year time-scale).[83] As CH_4 degrades in the upper atmosphere, it reacts with ozone to form water vapor and CO_2, which continues to warm the climate for centuries. Through the Methane Emissions Reduction Program, DOE's Office of Fossil Energy and Carbon Management (FECM), U.S. Environmental Protection Agency (EPA), and NETL are providing technical assistance and up to $1.3 billion in financial assistance to improve methane monitoring and to reduce methane and other GHG emissions from the oil and gas sector with the co-benefit of reducing non-GHG emissions, such as volatile organic compounds and hazardous air pollutants.

Key challenges to CH_4 mitigation include the broad geographic distribution of sources and intermittent nature of releases (often during abnormal operating conditions). The past 10 years have seen significant progress in detecting and quantifying CH_4 emissions at the source using surface-based technologies like hand-held and vehicle-based detection sensors, but these technologies cannot quickly assess large areas. Other technologies, such as atmospheric sensing equipment attached to satellites or manned and unmanned aircraft can better estimate the volume of CH_4 emissions across wide areas, but these measurements are not taken continuously, are typically less accurate in pinpointing sources than surface-based methods, and have higher detection limits, potentially missing smaller leaks.

AI/ML tools can improve the use of these technologies to better detect, quantify, abate, and prevent CH_4 emissions. An integrated CH_4 monitoring platform with AI models could curate and analyze CH_4 sensor data collected across various temporal frequencies, altitudes, and geographical ranges (local, basin, regional, and national scale) along with environmental data (wind speed and direction) and activity data to deliver accurate estimates of CH_4 emissions. That platform combined with research, development, demonstration, and deployment activities in CH_4 mitigation on undocumented/orphaned wells, pipeline integrity, geologic storage for H_2, and crosscutting issues could help mitigate the most severe impacts of CH_4 on climate change.[84]

3.5.3.1 Undocumented or Orphaned Wells

More than 100 years of oil and gas drilling in the United States have left thousands of wells undocumented or orphaned. Unfortunately, many are improperly sealed and allow liquids and gases to rise to the surface, including potent GHGs like CH_4.[85] BIL allocated $4.7 billion toward plugging, remediation and restoration activities of orphaned wells on Federal, Tribal, state and private lands.[86] Among other things, BIL directs DOE to conduct research to locate, identify, and characterize undocumented orphaned wells.[87]

Identifying the location of undocumented orphaned wells is generally a time-intensive and costly process. Initial efforts involve examining records in the form of logs, articles, files, floppy disks, microfiche, notebooks, maps, newspapers, photos, lease maps, and other records stored in dispersed locations across the public and private sector. Existing, well-established AI tools such as optical character recognition and natural language processing can help accurately transcribe, digitize, and format records to support future AI analysis that will help determine the locations of wells and assess the accuracy of those locations. AI can also interpret data on geomorphology, geography, and vegetation indices around known abandoned wells to predict likely sites of undocumented orphan wells. Combining multimodal data in this way will provide various types/contexts/sources of data to maximize and leverage all data components (including changes over time)—adding new layers of meaning and generating new insights. Ultimately, digitized legacy data, multimodal data, and historical well patterns may be integrated into a central database to expedite additional identification of currently unknown wells.

3.5.3.2 Pipeline Integrity

CH_4 emissions from pipelines are more difficult to detect and measure than those from more localized parts of the infrastructure like processing plants.[88] A significant hurdle is the immense geographic spread and diversity of the pipeline network. Leaks of CH_4 can occur by accident or during regular operations, such as venting, valve adjustments, or periodic maintenance. Given these varied causes, the emissions can fluctuate widely over time.[89] Leveraging AI, DOE is developing advanced mitigation solutions to detect, address, and prevent pipeline leakage.

3.5.4 Virtual Subsurface

Society's reliance on subsurface systems and resources (e.g., groundwater and minerals) has increased over the centuries and continues to grow. The subsurface currently provides over 80% of our energy and over 50% of the US groundwater.[90] The subsurface has additional potential to provide new, clean energy resources, unconventional critical minerals, geologic hydrogen, etc. It also offers significant potential to safely store resources (e.g., H_2, compressed air, etc.), and to dispose of carbon waste[91] and other energy byproducts. In the United States, the more than 4 million wellbores resulting from drilling for hydrocarbons now represent a treasure trove of direct and indirect information about the subsurface near each of these locations. A more complete and fine-grained understanding of subsurface characteristics will be key to accelerating identification and development of rare earth elements and critical minerals, storing energy, safely sequestering carbon dioxide waste, and predicting seismic hazards.

3.5.4.1 Enabling Enhanced Subsurface Mapping with AI

Despite the disparate and patchwork nature of subsurface knowledge and data, there is a significant opportunity for AI to accelerate development of a unified virtual subsurface data and knowledge system, providing a digital map for the subsurface. The Earth's subsurface is vast but still poorly understood, hindering exploration and resource utilization. Strides have been made in understanding the fundamental principles and processes resulting in present-day geologic systems despite limited samples and indirect measurements. Predicting properties like temperature or porosity is riddled with variability and high uncertainty. Even well-explored regions have vast unknowns, hindering safe and efficient exploration. To accurately forecast subsurface energy resources and emissions, models require accurate input parameters which are difficult to obtain due to the challenge of interrogating the subsurface.

Where data is plentiful, AI may help identify which data types are most valuable for specific applications. [*See Inset: "Spotlight: Secure Underground Hydrogen Storage"*] AI/ML can bring together geologic data from a variety of sources (maps, reports, or logs from state, industry, or regulatory groups) and of various types (permeability, temperature, porosity, rock properties, pressure, etc.). Where data is sparse, AI/ML can help researchers use the available data to fill in the gaps with high-fidelity digital twins or appropriate synthetic and/or analog data, apply transfer learning, identify the limits of extrapolation for different subsurface environments, and help select new data types including through advanced generative AI techniques to improve assessment accuracy. AI/ML can apply pattern recognition to massive datasets

Spotlight: Secure Underground Hydrogen Storage

AI can help characterize potential underground sites for H_2 storage and cycling and to predict and prevent leaks through accurate modeling and monitoring to ensure reliable containment and safe and efficient operation.

Depleted natural gas fields represent a promising option for H_2 storage and AI could help characterize and assess subsurface natural gas storage sites to determine the feasibility of types of formations or specific sites for conversion to H_2 storage. Existing subsurface models for those storage sites may provide a useful starting point for modeling underground H_2 storage. AI transfer learning techniques (reuse of a pre-trained model on a new problem, i.e., H_2) as well as synthetic data generation could potentially uncover patterns in the available data on a wide range of existing subsurface natural gas storage sites (including volume, permeability, porosity, long-term caprock integrity, injectivity, seismic activity risk, cushion gas levels, well design, production rates, management issues, etc.).

to significantly reduce the interpretation time, potentially leading to near-real-time interpretation of field monitoring data. Finally, AI/ML can significantly improve the critical decision-making process, including near-real-time decisions, related to field operations through rapid predictions and scenario analysis.

3.5.4.2 Building Digital Twins of the Subsurface

Diverse sources and types of data are necessary to build an understanding of complex and varied subsurface systems. Aggregating existing data and combining it with knowledge-based information about these systems and properties can inform ongoing subsurface exploration activities and respond to changing demands society is placing on subsurface systems. An adaptive and integrated virtualized digital twin and enabling computational infrastructure are needed to support real-time, rapid, and multi-scale simulation and forecasting to build the clean energy economy of the United States, mitigate GHG emissions, and optimize security and deployment of energy infrastructure.

While data and tools do not yet exist to create a complete digital planet twin, aggregation of what does exist, and authoritative integration, presents an opportunity to accelerate these goals and understand key gaps. Existing science-based models and tools[92] present a significant opportunity to serve as the building blocks for a comprehensive model that accelerates carbon management, climate, commercial, and societal goals.

Integration of measured data with coupled, knowledge-based, and AI-informed predictions where data are limited can achieve a new frontier for discovery in subsurface systems. Developing a first-of-its-kind virtual subsurface system will inform and enable responsible, AI-accelerated compliance with energy, environmental, and societal needs from the subsurface including, i) geohazard forecasting, such as natural and induced seismicity, ii) land-use decision making, iii) groundwater use, including impacts of discharge, and enhanced understanding of climate cycle and hydrological cycle, iv) mineral resource discovery, such as primary and alternative sources of rare earth elements and other critical minerals, geothermal resources and more, and v) informing safe and reliable subsurface storage for clean energy deployments, as well as subsurface storage for disposal of CO_2 and other fluids, enabling the return of previously geologically stored carbon (released through fossil fuel use) back to the subsurface.

4. Considerations for Widespread Deployment of AI Solutions

The disruptive innovation and deployment of any emerging technology always comes with consequences. Thoughtful consideration of how AI deployment affects different stakeholders and industries can mitigate later societal backlash or unforeseen hazards. Like many other industrial technologies, AI uses a significant amount of electricity. DOE is proactively working to encourage energy efficient practices for AI data centers and better track the energy growth of this industry. While AI adoption continues to grow, it is important to ensure everyone has equal access to AI technology and its benefits. Conversely, special care should be taken to address disparate harms from AI. Finally, ensuring the U.S. has an AI-ready workforce will afford everyone an opportunity to benefit from this industry and maintain the U.S. competitive edge in a skilled and scientific workforce.

4.1 Balancing AI Risks and Benefits

4.1.1 Tracking the Climate and Environmental Impacts of AI.

Within the US, data centers account for up to 3% of total electricity consumption. Global data center electricity usage in recent years has been about 1% of global consumption, growing about 6% between 2010 and 2018. However, during that same period computing capacity grew 550%.[93] Energy consumption has not grown linearly with datacenter capacity due to large hardware improvements, increases in Power Usage Effectiveness (PUE),[94] and shifts to cloud data centers moderating load growth. While AI has not been a significant contributor of data center-related electricity consumption historically, work currently underway at DOE's Lawrence Berkeley National Laboratory (LBNL) indicates that over half of data center load growth in recent years may have been due to AI, and it is expected to be the biggest driver of U.S. data center-related load growth in the near future.

There is already significant interest in the tech sector to reduce the GHG footprint of data centers and AI-related energy usage. Hyperscalers[95] have long leaned on power purchase agreements (PPAs) with wind and solar generators to offset the GHGs associated with their direct electricity usage. These agreements can offset electricity consumption with purchased renewable energy, but these PPAs typically do not match electricity demand hour by hour with local resources. Hence, there is no guarantee that all electricity-related GHG emissions are offset even if total electricity is offset by renewable energy credits if no hourly matching is required. In recent years companies have begun matching their load hour by hour with local clean energy resources to offset their total carbon footprint from direct electricity consumption. Similarly, shifting flexible workloads to hours when local renewable resources are plentiful and switching from diesel generators to solar and battery back-up offer opportunities for reduced fossil fuel consumption.

There are also concerns about the embodied emissions associated with the raw materials and manufacturing of the data centers themselves. Because of the high replacement rate of data center equipment, particularly servers, these embodied emissions from non-operational aspects of data centers should be a priority for analysis. Similarly, the rapid advancement of AI technologies may generate significant amounts of electronic waste that can be detrimental to human health and the environment if not properly recycled. Water usage for cooling data centers is also gaining increased attention.

4.1.2 Technical Roadmap to Further Improvements in Data Center Efficiency

Companies are financially incentivized to decrease their power consumption, and many efforts are underway to make AI as energy efficient as possible by developing better hardware, optimizing algorithms, and deploying clean energy onsite. Computing efficiency improvements have been doubling every 2-3 years, and other energy efficiency improvements reflect advances in servers, storage, network infrastructure, and shifts to hyperscale and cloud data centers. At the state-of-the-art, both for commercial models and for open-source models, many techniques have been developed to increase energy efficiency and decrease computational demands and memory requirements. These techniques include quantization,[96] which uses fewer bits to store each parameter in the model, pruning and distillation,[97] which create models with fewer parameters from models with more parameters, and so-called state-space and mixture-of-experts methods[98] — alternative AI designs that use fewer parameters than their peers.

Many companies are making significant advances in increasing the energy efficiency of AI systems and data centers. Google's TPU v4 processor for AI training is reported to be 1.3-1.9 times more energy efficient than the industry standard Nvidia A100 GPU processor, both of which entered production in 2020 and used a seven-nanometer semiconductor manufacturing process.[99] This is representative of a significant trend which many industry analysts expect to continue:[100] the continued deployment of computing hardware specifically designed for AI workloads, which is usually far more efficient than general purpose processors. This trend continued in March 2024 when NVIDIA announced its new Blackwell platform that can run real-time generative AI on trillion-parameter large language models at up to 25x less cost and energy consumption than its predecessor.[101] Further in the future, new semiconductor designs and techniques, including those making use of photonic computing, computing using cryogenic and superconducting devices, and so-called neuromorphic materials, promise 10-100x better energy efficiency.[102] DOE's Argonne National Lab already supports AI-specific hardware through its AI testbed, which gives U.S. researchers early access to next-generation hardware while also supporting early-stage AI hardware companies which also offer energy efficiency improvements.[103] DOE national labs have built computing facilities with a near-perfect PUE of ~1.03, demonstrating a deployment roadmap for state-of-the-art data center energy efficiency.[104] DOE Office of Science is continuing to invest in these innovative technologies,[105] which are beginning to be commercialized by various companies. ARPA-E has developed the COOLERCHIPS program which targets the development of transformational energy efficient cooling technologies to reduce cooling energy by 90% and reduce or eliminate cooling water usage for high power chipsets (like AI) for next-generation conventional or modular data centers.[106] It is targeted that these technologies will keep the US in global leadership in energy efficient computing technologies.

4.1.3 Supporting Best Practices for Data Center Efficiency

Hyperscale data centers at places such as Google, Facebook, and Amazon are now quite energy efficient, and green data centers are slowly becoming the industry standard. In 2020, the average data center used only 37% of its energy for cooling and other needs other than powering the IT equipment. But further efficiency can be realized - the most energy-efficient data centers in the world use only 2-3% of their energy for such purposes.[107] For example, Frontier, DOE's new exascale supercomputer at Oak Ridge National Laboratory (ORNL), uses advanced liquid cooling and other state-of-the-art techniques to achieve this 3% goal.[108] DOE will continue to support and promote the adoption of best practices for data center efficiency and support efficiency standards to encourage transparency in the industry.

In addition to convening relevant stakeholders across industry, academia, and NGOs to address this problem, DOE is actively working to improve technical analysis of energy usage at data centers. DOE's Industrial Efficiency & Decarbonization Office is developing a proposal to expand staff support and technical analysis offerings and create a proactive outreach engagement strategy on data center efficiency. This would (1) expand technical analysis offered directly to data center operators to include the full range of data center types, (2) update best practices and efficiency strategies to reflect use of new computational equipment for AI purposes, and (3) develop technical analysis offerings and engagements specifically for utilities and public utilities commission staff on ways to manage data center load, encourage efficiency, and reduce infrastructure cost risks borne by other ratepayers. Additionally, the Center of Expertise for Energy Efficiency in Data Centers at LBNL helps Federal agencies and other organizations implement data center energy efficiency projects by supplying technical support, tools, best practices, analyses, and the introduction of new technologies. The associated Data Center Energy Practitioner (DCEP) program, a partnership between DOE and the data center industry, certifies energy practitioners qualified to evaluate the energy status and efficiency opportunities in data centers.

4.2 Avoiding Bias and Discrimination in AI and Promoting Civil Rights, Equity, and Environmental Justice

Among the great challenges of broader deployment of AI is the potential for those systems to be developed and deployed in ways that threaten the rights of Americans or undermine policy goals of equity and environmental justice. There are well documented problems with some AI systems (and other algorithmically automated systems) being deployed in ways that have been biased or discriminatory in a variety of contexts, including:

- Predictive policing tools based on data from periods of documented racially biased policing practices,[109] and/or re-offender risk scores that embed existing racial disparities;[110]
- Automatic screening tools for "higher-risk renters" or algorithms for mortgage lending decisions that disproportionately impact minority groups;[111]
- In job recruitment and hiring decisions;[112]
- An LLM providing advice that perpetuates unscientific racial tropes.[113]

The concerns about bias and discrimination apply in the electricity sector as well. For example, algorithms or AI systems that identify routes or sites for infrastructure that aim at identifying a "least cost" site are likely to identify areas of low property value or greater poverty for siting infrastructure, which could perpetuate ongoing impacts from redlining, exclusionary zoning, or other discriminatory land use decisions or patterns and could exacerbate existing environmental justice concerns.[114]

These biases may exist and persist in more subtle ways even where AI model developers are attempting to impose guardrails to prevent bias and discrimination. The developers of commercial LLMs have typically developed guardrails that prevent the LLMs from producing explicitly racist or discriminatory language (or that at least make it more difficult to elicit such output). But these LLMs can still produce biased results and do so even if the race or ethnicity or other demographics of an individual is not specified in questions to the LLM. [115]

To address these problems, EO 14110 outlines guidance for agencies and specifies a number of actions for agencies to take to combat bias in AI and protect civil rights, such as exploring authorities that agencies have to prevent algorithmic bias, publishing plans and guidance for state, local, and tribal authorities to prevent bias in any automated systems used for distributing benefits, and issuing guidance on the use of AI in housing decisions. Best practices developed in those contexts can help inform appropriate development of AI systems for energy. Also, the White House Office of Science and Technology Policy has released a Blueprint for an AI Bill of Rights to guide agencies[116] highlighting five principles: 1) Safe and Effective Systems, 2) Algorithmic Discrimination Protections, 3) Data Privacy, 4) Notice and Explanation, 5) Human Alternatives Consideration and Fallback.

AI systems also have the potential to improve energy equity and environmental justice. DOE has prioritized ensuring the benefits from clean energy solutions flow to disadvantaged communities that are marginalized by underinvestment and overburdened by pollution. This includes communities that are disproportionately impacted by polluted air and water, are most vulnerable to inadequate or costly energy supplies, and are more vulnerable to extreme weather events. Such communities facing environmental injustice are often lower income and are disproportionately Black, Brown, and Indigenous.

An increased focus on data gathering, processing, and visualization has improved the ability to identify disadvantaged communities, energy justice communities, and other communities with environmental justice concerns. These new tools can help track the benefits and burdens of energy development on affected communities.[117] These improved data sets and screening tools have been utilized to shed more light on past energy inequities – such as the fact that disadvantaged communities have received 37% fewer funds per capita of historic Federal energy investments compared to non-disadvantaged communities.[118] Most existing data sets only resolve to the census tract (or sometimes census block) level and are not available at a higher resolution. Where researchers have been able to obtain more high-resolution data, their work has indicated that disparities in energy equity (measured by energy use intensity in households) based on income and race were up to six-fold more severe than indicated by lower resolution data.[119]

AI and ML models that can help develop and interpret more fine-grained data on energy inequity and environmental justice, and can assist utilities, non-profits, and government at all levels (Federal, state, and local) better target their interventions, inventions, and initiatives.[120] Some examples from existing research include studies that helped show the racial disparities in the installation of rooftop solar[121] and develop street-by-street mapping of temperature extremes.[122] Oak Ridge National Laboratory has also developed modeling that can help assess climate vulnerability in urban neighborhoods down to the street and building level, including information that enables assessment of equity and environmental justice impacts.[123]

4.3 Ensuring a Technically Skilled Supply of AI Talent

An AI-ready workforce is essential for the United States to fully realize AI's potential to advance scientific discovery, economic prosperity, and national security. Executive Order 14110 calls for the DOE, in coordination with the U.S. National Science Foundation (NSF), to "establish a pilot program to enhance existing successful training programs for scientists, with the goal of training 500 new researchers by 2025 capable of meeting the rising demand for AI talent."

Over the course of its history, DOE has trained thousands of future scientists to be AI research leaders through graduate, post-graduate, and staff opportunities at the network of DOE National Labs, leveraging decades of sustained R&D investments in high-performance computing that have led to significant advances in both fundamental studies and world-leading supercomputing tools. AI researchers at DOE National Laboratories have introduced basic AI concepts and skills to hundreds of thousands of students and educators at all levels. Training programs at DOE national laboratories deliver opportunities for best-in-class hands-on research experiences, including through access to leading AI research expertise, world-class supercomputing facilities, and a science-driven approach. These training opportunities complement AI education and training offered through other pathways, such as AI education and training supported by both DOE and NSF at institutions of higher education and various other settings for learning.

The unparalleled research and innovation environment at DOE National Laboratories attracts talent from all over the world to strengthen America's AI workforce. DOE will continue its investments in a highly skilled talent pool - encompassing K-12 educators and students, undergraduate and graduate students, postdoctoral researchers, and faculty and professionals looking to add to their skillsets - to grow and sustain America's AI-ready workforce of tomorrow.

Leveraging its AI research investment and broad STEM education portfolio, NSF has supported the creation of educational tools, curricula and materials, undergraduate research experiences, graduate fellowships/traineeships, and early career scientist awards to enhance learning and foster training opportunities in AI related areas. DOE is coordinating with NSF to reinvigorate the potential in the United States for building AI skills and knowledge at all levels needed to responsibly harness the opportunities of AI for scientific discovery and other critical societal challenges, such as policy and governance.

DOE recognizes that the broader STEM workforce and its associated talent pool is less diverse than the general United States population, and that digital advances related to AI may further deepen the gap for communities and groups historically underrepresented and marginalized in the science and technology enterprise of the United States. DOE is working with NSF, other Federal agencies, and industry partners to enable equitable access and pathways to high-quality AI learning experiences and support better preparation for pursuing AI career opportunities.

By 2025, the education and workforce opportunities provided by the DOE and NSF pilot program will add to the national AI workforce by training more than 500 new researchers at all career stages in a variety of critical basic research and enabling technology development areas.

DOE, in coordination with NSF, is creating a vibrant training and workforce ecosystem by advancing secure, trustworthy, and equitable AI for all Americans. The Supercharging America's AI Workforce web portal launched in February highlights a non-exhaustive collection of DOE and NSF AI education, training, and workforce opportunities.[124] This is a part of a larger effort to increase connectivity between government-supported AI learning and training programs and elevate the accessibility of these opportunities to people interested in accruing AI knowledge and skills.

4.4 Facilitating Security and Robustness of AI Deployed in Critical Energy Infrastructure.

While a number of significant risks to the electric system can 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. With this in mind, DOE's Office of Cybersecurity, Energy Security, and Emergency Response (CESER) will be expanding its engagement with energy sector partners on artificial intelligence, from the security and resilience perspective – while also working to identify areas of existing and upcoming programmatic focus, where artificial intelligence is a key consideration.

In coordination with energy sector stakeholders, CESER will examine the public availability of energy sector data and its potential to impact the security posture of owners or operators of energy infrastructure. This will include evaluating the potential for such data to be leveraged to enable cyber or physical attacks against energy infrastructure, including using AI tools.

CESER will also explore the ways in which AI can be leveraged by existing programs, such as the Energy Threat Analysis Center (ETAC), to ensure that they continue to operate at the speed and scale required by a changing energy system and dynamic risk landscape.[125] Potential areas of application include utilizing AI tools to enable machine-scale analysis of operational and IT data from energy systems, for potential risks.

For applications beyond critical energy infrastructure, DOE has also released an Artificial Intelligence Risk Management Playbook which includes additional examples of potential risks and mitigations, focused primarily on the use of AI in enterprise settings – which may also prove valuable for energy sector entities.[126]

Furthermore, DOE continues to invest in innovative approaches to ensuring the security and robustness of AI systems, such as privacy-enhancing technologies (PETs) for AI.[127] PETs include methods for AI training that are federated with added protections to prevent recovering training data from the resulting AI models. In this context, federated means that the training data can be distributed across many different systems and no one entity needs to have access to all of the data. While often thought of in the context of medical research, where PETs are employed to protect private data from patient's medical records, PETs can enable collaborative development of AI systems for energy infrastructure as well. Data from grid operators, materials manufacturers, regulators, and many other entities might be combined using PETs to enable the development and optimization of robust energy systems while protecting private and proprietary information. In February 2024, DOE joined NSF in creating a Research Coordination Network (RCN) for PETs. The RCN will help to facilitate exchange of best practices and innovative concepts between researchers across the country for the development and use of PETs for AI.[128]

5. Conclusion

DOE has long supported fundamental research in AI, particularly as it relates to energy R&D and the power grid. The recent development of powerful new AI foundation models poses the potential to accelerate clean energy deployment for a 100% clean power grid and to enable a clean energy economy. The thoughtful adoption of AI can drive energy innovation across the economy and help meet the Administration's climate goals. However, as with the introduction of any transformative industrial technology, the deployment of AI comes with significant energy use, the need for new workforce development, and the potential inequitable impacts on marginalized communities. This report outlines DOE's ongoing activities and the near-term potential to safely and ethically implement AI to enable a secure, resilient power grid and drive energy innovation across the economy, while providing a skilled AI-ready energy workforce.

Endnotes

[1] Theodore U. Marston, "The US Electric Power Infrastructure and Its Vulnerabilities," The Bridge 48, no. 2 (2018): 31–39, https://www.nae.edu/19579/19582/21020/183082/183133/The-US-Electric-Power-System-Infrastructure-and-Its-Vulnerabilities.

[2] "Gross Domestic Product, Fourth Quarter and Year 2023 (Second Estimate)," Bureau of Economic Analysis, February 28, 2024, https://www.bea.gov/news/2024/gross-domestic-product-fourth-quarter-and-year-2023-second-estimate

[3] "The Smart Grid: An Introduction," U.S. Department of Energy, 2008, https://www.energy.gov/oe/articles/smart-grid-introduction-0.

[4] "Secretary Granholm on the Biden-Harris Administration's Industrial Strategy for Clean Energy," U.S. Department of Energy, February 20, 2024, https://www.energy.gov/articles/remarks-delivered-secretary-jennifer-granholm-new-industrial-revolution-clean-energy.

[5] Adam B. Smith, "2023: A Historic Year of U.S. Billion-Dollar Weather and Climate Disasters," Beyond the Data, January 8, 2024, https://www.climate.gov/news-features/blogs/beyond-data/2023-historic-year-us-billion-dollar-weather-and-climate-disasters.

[6] The Paris Agreement refers to the Agreement adopted by the Parties to the United Nations Framework Convention on Climate Change (UNFCCC) at the 21st Conference of the Parties on December 12, 2015. See "Paris Agreement," conclusion date: December 12, 2015, United Nations, https://unfccc.int/files/essential_background/convention/application/pdf/english_paris_agreement.pdf.

[7] "The Evidence is Clear: The Time for Action is Now. We Can Halve Emissions by 2030," Intergovernmental Panel on Climate Change, April 4, 2022, https://www.ipcc.ch/2022/04/04/ipcc-ar6-wgiii-pressrelease.

[8] "The Long-Term Strategy of the United States: Pathways to Net-Zero Greenhouse Gas Emissions by 2050," United States Department of State and United States Executive Office of the President, November 2021, https://www.whitehouse.gov/wp-content/uploads/2021/10/us-long-term-strategy.pdf.

[9] DOE is guided by the principles of responsible AI outlined in the Executive Order. Joseph R. Biden, Jr., "Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence," The White House, October 30, 2023, https://www.whitehouse.gov/briefing-room/presidential-actions/2023/10/30/executive-order-on-the-safe-secure-and-trustworthy-development-and-use-of-artificial-intelligence; Shalanda D. Young, "Advancing Governance, Innovation, and Risk Management for Agency Use of Artificial Intelligence," *Office of Management and Budget* Memorandum M-24-10, March 28, 2024, https://www.whitehouse.gov/wp-content/uploads/2024/03/M-24-10-Advancing-Governance-Innovation-and-Risk-Management-for-Agency-Use-of-Artificial-Intelligence.pdf.

[10] Comments received in response to the RFI are available at: https://www.regulations.gov/document/DOE-HQ-2024-0007-0001.

[11] A 100% clean electricity system in the referenced studies is one having net zero GHG emissions. Some of the scenarios in the NREL report "Examining Supply-Side Options to Achieve 100% Clean Electricity by 2035" include generation sources that emit GHG with those emissions offset within the electricity sector by negative emitting sources such as biomass combustion with carbon capture and sequestration and/or direct air capture technologies. See Paul Denholm, Patrick Brown, Wesley Cole, et al., "Examining Supply-Side Options to Achieve 100% Clean Electricity by 2035," National Renewable Energy Laboratory, August 2022, https://www.nrel.gov/docs/fy22osti/81644.pdf.

[12] "Investing in American Energy: Significant Impacts of the Inflation Reduction Act and Bipartisan Infrastructure Law on the U.S. Energy Economy and Emissions Reductions," *U.S. Department of Energy*, August 2023, https://www.energy.gov/policy/articles/investing-american-energy-significant-impacts-inflation-reduction-act-and.

[13] "Table 7.7B Electric Net Summer Capacity: Electric Power Sector," U.S. Energy Information Administration, n.d., https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T07.07B#/?f=M.

[14] Denholm et al., "Examining Supply-Side Options."

[15] Ibid.

[16] Paul Donahoo-Vallett, Nicole Ryan, and Ryan Wiser, "On the Path to 100% Clean Electricity," U.S. Department of Energy, May 2023, https://www.energy.gov/sites/default/files/2023-05/DOE%20-%20100%25%20Clean%20Electricity%20-%20Final.pdf. The Key Actions are each quoted from that report.

[17] For more on balancing authority, see "How It Works: The Role of a Balancing Authority," U.S. Department of Energy, August 2023, https://www.energy.gov/sites/default/files/2023-08/Balancing%20Authority%20Backgrounder_2022-Formatted_041723_508.pdf.

[18] "The Smart Grid: An Introduction," U.S. Department of Energy.

[19] Rishi Bommasani et al., "On the Opportunities and Risks of Foundation Models," Center for Research on Foundation Models, pre-print, July 12, 2022, https://doi.org/10.48550/arXiv.2108.07258.

[20] "Dynamic Line Rating," U.S. Department of Energy, June 2019, https://www.energy.gov/oe/articles/dynamic-line-rating-report-congress-june-2019.

[21] Katie Siegner, Sarah Toth, Chaz Teplin, and Katie Mulvaney, "GETting Interconnected in PJM: Grid-Enhancing Technologies (GETs) Can Increase the Speed and Scale of New Entry from PJM's Queue," RMI, 2024, https://rmi.org/insight/analyzing-gets-as-a-tool-for-increasing-interconnection-throughput-from-pjms-queue.

[22] "Electrification Impacts Study Part 1: Bottom-Up Load Forecasting and System-Level Electrification Impacts Cost Estimates," *Kevala, Inc*., May 2023, https://www.kevala.com/resources/electrification-impacts-study-part-1.

[23] Shanti Pless, Amy Allen, Lissa Myers, et al., "Integrating Electric Vehicle Charging Infrastructure into Commercial Buildings and Mixed-Use Communities: Design, Modeling, and Control Optimization Opportunities," National Renewable Energy Laboratory, September 2020, https://www.nrel.gov/docs/fy20osti/77438.pdf.

[24] Jared Sagoff, "Argonne and University of Chicago Researchers Improve Management of Electric Vehicle Charging Through Machine Learning," Argonne National Laboratory, July 24, 2023, https://www.anl.gov/article/argonne-and-university-of-chicago-researchers-improve-management-of-electric-vehicle-charging.

[25] Joseph Rand, Rose Strauss, Will Gorman, et al., "Queued Up: Characteristics of Power Plants Seeking Transmission Interconnection As of the End of 2022," Lawrence Berkeley National Laboratory, April 2023, https://emp.lbl.gov/sites/default/files/emp-files/queued_up_2022_04-06-2023.pdf.

[26] The total generation capacity that requested interconnection each year has similarly increased from approximately 100 GW per year to over 500 GW in 2022 and 2023.

[27] Jeff St. John, "New Software Can Find More Room for Clean Energy on Electric Grids," Canary Media, August 23, 2022, https://www.canarymedia.com/articles/transmission/new-software-can-find-more-room-for-clean-energy-on-transmission-grid.

[28] Will Gorman, Jospeh Rand, Julia Matevosyan, and Fredrich Kahrl, "DOE Transmission Interconnection Roadmap: Transforming Bulk Transmission Interconnection by 2035," U.S. Department of Energy, April 2024, https://www.energy.gov/eere/i2x/doe-transmission-interconnection-roadmap-transforming-bulk-transmission-interconnection.

[29] St. John, "New Software Can Find."

[30] "Grid Modernization Initiative," U.S. Department of Energy, n.d., https://www.energy.gov/gmi/grid-modernization-initiative.

[31] "Grid Optimization Competition," ARPA-E, n.d., https://gocompetition.energy.gov.

[32] "Smart Grid Grants," U.S. Department of Energy, n.d., https://www.energy.gov/gdo/smart-grid-grants.

[33] "FACT SHEET: Biden-Harris Administration Outlines Priorities for Building America's Energy Infrastructure Faster, Safer, and Cleaner," The White House, May 10, 2023, https://www.whitehouse.gov/briefing-room/statements-releases/2023/05/10/fact-sheet-biden-harris-administration-outlines-priorities-for-building-americas-energy-infrastructure-faster-safer-and-cleaner.

[34] Robi Nilson, Ben Hoen and Joe Rand, "Survey of Utility-Scale Wind and Solar Developers Report," Lawrence Berkeley National Laboratory, January 2024, https://emp.lbl.gov/publications/survey-utility-scale-wind-and-solar.

[35] Katherine Young, Aaron Levine, Jeff Cook, et al., "GeoVision Analysis Supporting Task Force Report: Barriers: An Analysis of Non-Technical Barriers to Geothermal Deployment and Potential Improvement Scenarios," National Renewable Energy Laboratory, May 2019, https://www.nrel.gov/docs/fy19osti/71641.pdf.

[36] Eric O'Shaughnessy, Galen Barbose, and Ryan Wiser, "Patience is a Virtue: A Data-Driven Analysis of Rooftop Solar PV Permitting Timelines in the United States," Energy Policy 144 (September 2020): https://doi.org/10.1016/j.enpol.2020.111615.

[37] "Recommendations to Improve Mining on Public Lands," Interagency Working Group on Mining Laws, Regulations, and Permitting, September 2023, https://www.doi.gov/sites/doi.gov/files/mriwg-report-final-508.pdf.

[38] In 2021, the General Services Administration and Federal Chief Data Officers' Council conducted a pilot assessing the potential for language models to make comment processing. It estimated that a generalizable comment topic modeling tool could save 8 hours per 100 comments received. See "Implementing Federal-Wide Comment Analysis Tools: CDO Council Special Projects Final Recommendations," CDO Council, June 2021, https://resources.data.gov/assets/documents/CDOC_Recommendations_Report_Comment_Analysis_FINAL.pdf.

[39] Of those statutes, only the Clean Water Act is a permitting statute. Under the Endangered Species Act, no permit is issued but a review is conducted to ensure that the action in question will not jeopardize the survival of a threatened or endangered species. NEPA provides opportunity for public and community engagement and develops information on potential impacts to the environment to better inform decisions. The National Historic Preservation Act established processes for the protection of the Nation's historic properties.

[40] NEPAccess.org. Northwestern University Transportation Library also maintains a collection of EISs dating to the beginning of NEPA that were digitized in cooperation with Google and are available online with full-text searchability through the Hathi Trust: "Environmental Impact Statement Collection," Northwestern University, n.d., https://libguides.northwestern.edu/environmentalimpactassessment.

[41] Matei Zaharia, Omar Khattab, Lingjiao Chen, et al., "The Shift from Models to Compound AI Systems," Berkeley Artificial Intelligence Research, February 18, 2024, https://bair.berkeley.edu/blog/2024/02/18/compound-ai-systems.

[42] AI4 Energy report identifies reforming the licensing and permitting process for advanced reactors as one of the three grand challenges for Nuclear Energy and describes in more detail the potential development of such models (report forthcoming).

[43] Michael Armbrust, Ali Ghodsi, Reynold Xin, and Matei Zaharia, "Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics," 11th Annual Conference on Innovative Data Systems Research (CIDR '21), January 11–15, 2021, https://www.databricks.com/research/lakehouse-a-new-generation-of-open-platforms-that-unify-data-warehousing-and-advanced-analytics.

[44] "Fire Protection Data Trends, Calendar Years 2015-2019," U.S. Department of Energy, December 2021, https://www.energy.gov/sites/default/files/2022-07/US%20DOE%20Fire%20Protection%20Data%20Trends%20CY%202015-2019%20-%20December%202021.pdf.

[45] The average U.S. customer loses power less than two times per year for a total of less than five hours. See Paul Denholm, "Top 10 Things To Know About Power Grid Reliability," National Renewable Energy Laboratory, January 26, 2024, https://www.nrel.gov/news/program/2024/top-10-things-to-know-about-power-grid-reliability.html.

[46] E.g. the Common Information Model: Alexander A. Anderson, Thomas E. McDermott, and Eric. G. Stephan, "A Power Application Developer's Guide to the Common Information Model: An Introduction for Power Systems Engineers and Application Developers – CIM17v40," Pacific Northwest National Laboratory, March 2023, https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-34946.pdf.

[47] Physics-informed approaches embed known physical equations into neural network training. Physics-informed AI is a subset of techniques for domain-aware AI, which incorporates domain knowledge into model training.

[48] For instance, DOE jointly funded research with NASA and the U.S. Geological Survey to use AI to provide advanced warning of solar geomagnetic events, which could adversely affect the grid: Vanessa Thomas, "NASA-Enabled AI Predictions May Give Time to Prepare for Solar Storms," National Aeronautics and Space Administration, March 30, 2023, https://www.nasa.gov/science-research/heliophysics/nasa-enabled-ai-predictions-may-give-time-to-prepare-for-solar-storms.

[49] "N-1 contingency" describes a situation where a single principal component fails, e.g., a single distribution line faults in a network. See Hongming Zhang, Slaven Kincic, and Sherrill Edwards, Advanced Power Applications for System Reliability Monitoring (Switzerland: Springer Nature, 2021): 15-16.

[50] "North American Energy Resilience Model (NAERM)," U.S. Department of Energy, n.d., https://www.energy.gov/oe/north-american-energy-resilience-model-naerm.

[51] "Big Data Synchrophasor Analysis," U.S. Department of Energy, n.d., https://www.energy.gov/oe/big-data-synchrophasor-analysis.

[52] "Energy Department Announces $7 Million Funding Opportunity for Grid-Enhancing Data Analytics Demonstrations," U.S. Department of Energy, December 12, 2023, https://www.energy.gov/oe/articles/energy-department-announces-7-million-funding-opportunity-grid-enhancing-data-analytics.

[53] "FERC Order No. 2222 Explainer: Facilitating Participation in Electricity Markets by Distributed Energy Resources," Federal Energy Regulatory Commission, June 14, 2023, https://www.ferc.gov/ferc-order-no-2222-explainer-facilitating-participation-electricity-markets-distributed-energy.

[54] "Billion-Dollar Weather and Climate Disasters," NOAA National Centers for Environmental Information, 2024, https://www.ncei.noaa.gov/access/billions.

[55] "Climate Mapping for Resilience & Adaptation," U.S. Global Change Research Program, n.d., https://resilience.climate.gov.

[56] "Resource Adequacy," National Renewable Energy Laboratory, n.d., https://www.nrel.gov/research/resource-adequacy.html.

[57] For example, IARPA funded a competition to detect backdoored models: "TrojAI: Trojans in Artificial Intelligence," IARPA, n.d., https://www.iarpa.gov/research-programs/trojai.

[58] "CESER Releases Supply Chain Assessment on Digital Components," U.S. Department of Energy, March 7, 2022, https://www.energy.gov/ceser/articles/ceser-releases-supply-chain-assessment-digital-components.

[59] "Sources of Greenhouse Gas Emissions," U.S. Environmental Protection Agency, 2024, https://www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

[60] Ibid.

[61] Ibid.

[62] Ibid.

[63] "Basic Energy Sciences (BES)," U.S. Department of Energy, n.d., https://www.energy.gov/science/bes/basic-energy-sciences.

[64] Jennifer Downing, Nicholas Johnson, Mailinh McNicholas, et al., "Pathways to Commercial Liftoff: Virtual Power Plants," U.S. Department of Energy, September 2023, https://liftoff.energy.gov/vpp.

[65] "Grid-Interactive Efficient Buildings," U.S. Department of Energy, n.d., https://www.energy.gov/eere/buildings/grid-interactive-efficient-buildings.

[66] Sam Goldman, Paul Majsztrik, Isabelle Sgro Rojas, et al., "Pathways to Commercial Liftoff: Low-Carbon Cement," U.S. Department of Energy, September 2023, https://liftoff.energy.gov/wp-content/uploads/2023/09/20230918-Pathways-to-Commercial-Liftoff-Cement.pdf.

[67] Tsisilile Barlock et al., "Supply Chains Progress Report," U.S. Department of Energy, n.d., https://www.energy.gov/sites/default/files/2023-08/Supply%20Chain%20Progress%20Report%20-%20August%202023.pdf.

[68] Katheryn Scott, Andrew Gilbert, Joshua Freeman, et al., "Pathways to Commercial Liftoff: Industrial Decarbonization," U.S. Department of Energy, September 2023, https://liftoff.energy.gov/industrial-decarbonization.

[69] Mik Carbajales-Dale and Hao Chen, "An Inverse Design Methodology to Fabricate Low-Cost Agile Tools for Manufacturing Lightweight Automotive Components," n.d., Clemson Energy-Economy-Environment (E3) Systems Analysis Group, https://e3sa.sites.clemson.edu/Projects/InverseDesign.html.

[70] "Department of Energy Awards $2 Million in Funding for Smart Manufacturing Technologies," U.S. Department of Energy, November 4, 2022, https://www.energy.gov/eere/ammto/articles/department-energy-awards-2-million-funding-smart-manufacturing-technologies.

[71] Meimei Li, David Andersson, Ryan Dehoff, et al., "Advanced Materials and Manufacturing Technologies (AMMT): 2022 Roadmap," U.S. Department of Energy, https://www.energy.gov/ne/articles/advanced-materials-and-manufacturing-technologies-2022-roadmap.

[72] Alp Kucukelbir, "Manufacturing Sector," in Artificial Intelligence for Climate Change Mitigation Roadmap (ICEF Innovation Roadmap Project, December 2023), https://www.icef.go.jp/wp-content/uploads/2024/02/AI-Climate-Roadmap-ICEF-Dec-1-2023.pdf.

[73] Tiffany Plate, "American-Made Solar Prize Round 5 Finalists Have Been Announced," National Renewable Energy Laboratory, April 26, 2022, https://www.nrel.gov/news/program/2022/american-made-solar-prize-round-5-finalists-have-been-announced.html.

[74] "Artificial Intelligence and Machine Learning for Bioenergy Research: Opportunities and Challenges," U.S. Department of Energy, August 2022, https://doi.org/10.2172/1968870.

[75] Lynn Wendt, "Applying AI to Ag: INL Yield Mapping Tool Offers Growers New Opportunities," U.S. Department of Energy, January 6, 2023, https://www.energy.gov/eere/bioenergy/articles/applying-ai-ag-inl-yield-mapping-tool-offers-growers-new-opportunities.

[76] "Precision Agriculture using Networks of Degradable Analytical Sensors (PANDAS)," ARPA-E, n.d., https://arpa-e.energy.gov/technologies/projects/precision-agriculture-using-networks-degradable-analytical-sensors-pandas.

[77] Catherine Bolgar, "Discoveries in Weeks, Not Years: How AI and High-Performance Computing Are Speeding Up Scientific Discovery," Microsoft, January 9, 2024, https://news.microsoft.com/source/features/sustainability/how-ai-and-hpc-are-speeding-up-scientific-discovery.

[78] Benjamin Burger, Phillip Maffettone, Vladimir Gusev, et al., "A Mobile Robotic Chemist," Nature 583 (2020): 237–241, https://doi.org/10.1038/s41586-020-2442-2.

[79] Kelsey L. Snapp, Benjamin Verdier, Aldair Gongora, et al., "Autonomous Discovery of Tough Structures," pre-print, August 2023, https://doi.org/10.48550/arXiv.2308.02315.

[80] Fazel Bateni, Sina Sadeghi, Negin Orouji, et al., "Smart Dope: A Self-Driving Fluidic Lab for Accelerated Development of Doped Perovskite Quantum Dots," Advanced Energy Materials 14, no. 1 (2024): https://doi.org/10.1002/aenm.202302303.

[81] "Hydrogen Shot," U.S. Department of Energy, n.d., https://www.energy.gov/eere/fuelcells/hydrogen-shot.

[82] "Delivering on the U.S. Methane Emissions Reduction Action Plan," The White House, November 22, www.whitehouse.gov/wp-content/uploads/2022/11/US-Methane-Emissions-Reduction-Action-Plan-Update.pdf.

[83] "What's the Deal with Methane?" UN Environment Programme, October 18, 2022, www.unep.org/news-and-stories/video/whats-deal-methane.

[84] For more on AI and methane, see "Artificial Intelligence for the Methane Cycle Workshop Report," U.S. Department of Energy, March 2024, https://ess.science.energy.gov/ai4ch4.

[85] "DOE Awards $35 Million for Technologies to Reduce Methane Emissions," U.S. Department of Energy, December 2, 2021, www.energy.gov/articles/doe-awards-35-million-technologies-reduce-methane-emissions.

[86] "Orphaned Wells," U.S. Department of Interior, n.d., https://www.doi.gov/orphanedwells.

[87] "Undocumented Orphaned Wells Research Program Division of Methane Mitigation Technologies," U.S. Department of Energy, n.d., https://www.energy.gov/fecm/undocumented-orphaned-wells-research-program-division-methane-mitigation-technologies.

[88] Jevan Yu, Benjamin Hmiel, David R. Lyon, et al., "Methane Emissions from Natural Gas Gathering Pipelines in the Permian Basin," Environmental Science and Technology Letters 9, no. 11 (2022): 877-996, https://doi.org/10.1021/acs.estlett.2c00380; Dan Yang, Xinyi Zhang, Ti Zhou, et al., "A Novel Pipeline Corrosion Monitoring Method Based on Piezoelectric Active Sensing and CNN," Sensors 23, no. 2 (2023): 855, https://doi.org/10.3390/s23020855.

[89] Rebecca Leber, "It's Time to Freak Out About Methane Emissions," Vox, November 3, 2021, www.vox.com/22613532/climate-change-methane-emissions.

[90] H. S. Viswanathan, J. Ajo-Franklin, J. T. Birkholzer, et al., "From Fluid Flow to Coupled Processes in Fractured Rock: Recent Advances and New Frontiers," Reviews of Geophysics 60, no. 1 (March 2022): https://doi.org/10.1029/2021RG000744.

[91] "Strategic Vision: The Role of Fossil Energy and Carbon Management in Achieving Net-Zero Greenhouse Gas Emissions," U.S. Department of Energy, April 2022, https://www.energy.gov/fecm/strategic-vision-role-fecm-achieving-net-zero-greenhouse-gas-emissions.

[92] See, e.g., some examples, including data and knowledge resources for energy sources, emissions, and infrastructure, indexed on the Energy Data eXchange's (EDX) disCO2ver: "disCO2ver," EDX, n.d., https://edx.netl.doe.gov/sites/disco2ver-alpha.

[93] Eric Masanet, Arman Shehabi, Nuoa Lei, et al., "Recalibrating Global Data Center Energy-Use Estimates," Science 367, no. 6481 (2020): 984-986, https://doi.org/10.1126/science.aba3758.

[94] Power Usage Effectiveness (PUE) is a metric representing the ratio of total energy a data center uses compared to the energy consumed by its IT equipment alone. Hence, a PUE of 1.2 signals that the amount of energy used for cooling equipment, lighting, and other overhead energy activities is equal to 20% of the energy used for actual IT equipment.

[95] Hyperscalers are the operators of hyperscale data centers – massive, centralized data centers currently generally defined as having at least 5,000 servers and covering at least 10,000 square feet.

[96] Shuming Ma, Hongyu Wang, Lingxiao Ma, et al., "The Era of 1-Bit LLMs: All Large Language Models are in 1.58 Bits," pre-print, February 27, 2024, https://doi.org/10.48550/arXiv.2402.17764.

[97] Cheng-Yu Hsieh, Chun-Liang Li, Chih-Kuan Yeh, et al., "Distilling Step-by-Step! Outperforming Larger Language Models with Less Training Data and Smaller Model Sizes," pre-print, July 5, 2023, https://doi.org/10.48550/arXiv.2305.02301.

[98] Quentin Anthony, Yury Tokpanov, Paolo Glorioso, and Beren Millidge, "BlackMamba: Mixture of Experts for State-Space Models," pre-print, February 1, 2024, https://doi.org/10.48550/arXiv.2402.01771.

[99] Norman P. Jouppi, George Kurian, Sheng Li, et al., "TPU v4: An Optically Reconfigurable Supercomputer for Machine Learning with Hardware Support for Embeddings," pre-print, April 20, 2023, https://doi.org/10.48550/arXiv.2304.01433.

[100] Morgan Stanley estimates that the market for chips that have been specifically designed for AI is projected to account for 30% of the overall AI chip market by 2027. See Harsh Chauhan, "A Wall Street Analyst Believes This Semiconductor Stock Is Better Than Nvidia, and It Could Jump an Impressive 71%," The Motley Fool, January 26, 2024, https://www.nasdaq.com/articles/a-wall-street-analyst-believes-this-semiconductor-stock-is-better-than-nvidia-and-it-could.

[101] "NVIDIA Blackwell Platform Arrives to Power a New Era of Computing," NVIDIA Newsroom, March 18, 2024, https://nvidianews.nvidia.com/news/nvidia-blackwell-platform-arrives-to-power-a-new-era-of-computing.

[102] Minyi Xu, Xinrui Chen, Yehao Guo, et al., "Reconfigurable Neuromorphic Computing: Materials, Devices, and Integration," Advanced Materials 35, no. 51 (December 2023): https://doi.org/10.1002/adma.202301063. For photonic computing, see Maxwell G. Anderson, Shi-Yuan Ma, Tianyu Wang, et al., "Optical Transformers," pre-print, February 20, 2023, https://doi.org/10.48550/arXiv.2302.10360.

[103] "ALCF AI Testbed," Argonne Leadership Computing Facility, n.d., https://www.alcf.anl.gov/alcf-ai-testbed.

[104] Justin L. Whitt, "Update on Exascale Systems – Frontier," Oak Ridge National Laboratory, July 2022, https://science.osti.gov/-/media/ascr/ascac/pdf/meetings/202207/UpdateFrontier_ASCAC_202207.pdf; "High-Performance Computing Data Center Power Usage Effectiveness," *National Renewable Energy Laboratory*, n.d., https://www.nrel.gov/computational-science/measuring-efficiency-pue.html.

[105] "Department of Energy Announces $2 Million for Neuromorphic Computing Research," U.S. Department of Energy, September 10, 2020, https://www.energy.gov/science/articles/department-energy-announces-2-million-neuromorphic-computing-research.

[106] "Cooling Operations Optimized for Leaps in Energy, Reliability, and Carbon Hyperefficiency for Information Processing Systems," ARPA-E, September 22, 2022, https://arpa-e.energy.gov/technologies/programs/coolerchips.

[107] "What's the Best PUE Ratio for Data Centers?" Sunbird, March 9, 2022, https://www.sunbirddcim.com/blog/whats-best-pue-ratio-data-centers.

[108] Justin L. Whitt, "Frontier Overview," Oak Ridge National Laboratory, October 2022, https://www.olcf.ornl.gov/wp-content/uploads/2022-OLCF-User-Meetig-Overview-of-Frontier-Whitt.pdf.

[109] Rashida Richardson, Jason M. Schultz, and Kate Crawford, "Dirty Data, Bad Predictions: How Civil Rights Violations Impact Police Data, Predictive Policing Systems, and Justice," New York University Law Review 192 (2019): https://www.nyulawreview.org/online-features/dirty-data-bad-predictions-how-civil-rights-violations-impact-police-data-predictive-policing-systems-and-justice.

[110] Julia Angwin, Jeff Larson, Surya Mattu, and Lauren Kirchner, "Machine Bias," ProPublica, May 23, 2016, https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing.

[111] Valerie Schneider, "Locked Out by Big Data: How Big Data, Algorithms, and Machine Learning May Undermine Housing Justice," Columbia Human Rights Law Review 52, no. 1 (2020): https://hrlr.law.columbia.edu/hrlr/locked-out-by-big-data-how-big-data-algorithms-and-machine-learning-may-undermine-housing-justice; Emmanuel Martinez and Lauren Kirchner, "The Secret Bias Hidden in Mortgage-Approval Algorithms," Associated Press, August 25, 2021, https://apnews.com/article/lifestyle-technology-business-race-and-ethnicity-mortgages-2d3d40d5751f933a88c1e17063657586.

[112] Zhisheng Chen, "Ethics and Discrimination in Artificial Intelligence-Enabled Recruitment Practices," Humanities and Social Sciences Communications 10, 567 (2023): https://doi.org/10.1057/s41599-023-02079-x.

[113] Jesutofunmi A. Omiye, Jenna C. Lester, Simon Spichak, et al., "Large Language Models Propagate Race-Based Medicine," npj Digital Medicine 6, 195 (2023): https://doi.org/10.1038/s41746-023-00939-z.

[114] Joseph R. Biden, Jr., "Executive Order on Revitalizing Our Nation's Commitment to Environmental Justice for All," The White House, April 21, 2023, https://www.whitehouse.gov/briefing-room/presidential-actions/2023/04/21/executive-order-on-revitalizing-our-nations-commitment-to-environmental-justice-for-all.

[115] Amit Haim, Alejandro Salinas, and Julian Nyarko, "What's in a Name? Auditing Large Language Models for Race and Gender Bias," pre-print, February 29, 2024, https://doi.org/10.48550/arXiv.2402.14875; Valentin Hofmann, Pratyusha Ria Kalluri, Dan Jurafsky, and Sharese King, "Dialect Prejudice Predicts AI Decisions About People's Character, Employability, and Criminality," pre-print, March 1, 2024, https://doi.org/10.48550/arXiv.2403.00742.

[116] "Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People," The White House, October 2022, https://www.whitehouse.gov/ostp/ai-bill-of-rights.

[117] Federal agencies are using the Climate and Economic Justice Screening Tool to help identify disadvantaged communities. In addition, agencies are also using DOE's Energy Justice Dashboard and EPA's EJScreen tool to identify relevant communities. See "Climate and Economic Justice Screening Tool," Council on Environmental Quality, n.d., https://screeningtool.geoplatform.gov; "Energy Justice Dashboard (BETA)," U.S. Department of Energy, n.d., https://www.energy.gov/justice/energy-justice-dashboard-beta; "EJScreen: Environmental Justice Screening and Mapping Tool," U.S. Environmental Protection Agency, n.d., https://www.epa.gov/ejscreen.

[118] Natalie Popovich, Anjuli Jain Figueroa, Deborah Ann Sunter, and Monisha Shah, "Identifying Disadvantaged Communities in the United States: An Energy-Oriented Mapping Tool that Aggregates Environmental and Socioeconomic Burdens," Energy Research and Social Science 109 (March 2024): https://doi.org/10.1016/j.erss.2023.103391.

[119] Kangkang Tong, Anu Ramaswami, Corey (Kewei) Xu, et al., "Measuring social equity in urban energy use and interventions using fine-scale data," Proceedings of the National Academy of Sciences of the United States of America 118, no. 24 (2021): https://doi.org/10.1073/pnas.2023554118.

[120] "Energy Equity: Opportunities for Data Science, Machine Learning & AI Policy Impact in the US," DataKind, August 2023, https://www.datakind.org/wp-content/uploads/2023/08/DataKind-US-Energy-Equity-Landscape-2.pdf

[121] Deborah A. Sunter, Sergio Castellanos, and Daniel M. Kammen, "Disparities in Rooftop Photovoltaics Deployment in the United States by Race and Ethnicity," Nature Sustainability 2 (2019): 71-76, https://doi.org/10.1038/s41893-018-0204-z.

[122] Vivek Shandas, Jackson Voelkel, Joseph Williams, and Jeremy Hoffman, "Integrating Satellite and Ground Measurements for Predicting Locations of Extreme Urban Heat," Climate 7, no. 1 (2019): 5, https://doi.org/10.3390/cli7010005.

[123] "Scientists Develop Environmental Justice Lens to Identify Neighborhoods Vulnerable to Climate Change," Oak Ridge National Laboratory, June 1, 2022, https://www.ornl.gov/news/scientists-develop-environmental-justice-lens-identify-neighborhoods-vulnerable-climate-change.

[124] "Supercharging America's AI Workforce," U.S. Department of Energy, n.d., https://www.energy.gov/cet/supercharging-americas-ai-workforce.

[125] "Energy Threat Analysis Center," U.S. Department of Energy, n.d., https://www.energy.gov/ceser/energy-threat-analysis-center-0.

[126] "DOE AI Risk Management Playbook (AIRMP)," U.S. Department of Energy, n.d., https://www.energy.gov/ai/doe-ai-risk-management-playbook-airmp.

[127] One such investment is in the Advanced Privacy-Preserving Federated Learning Framework, known as APPFL. For additional information, see https://github.com/APPFL/APPFL.

[128] "NSF and DOE Establish a Research Coordination Network Dedicated to Enhancing Privacy Research," U.S. National Science Foundation, February 26, 2024, https://new.nsf.gov/news/nsf-doe-establish-research-coordination-network.

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