U.S. DEPARTMENT of ENERGY

DRAFT REPORT

Microgrids R&D Strategic Plan

Topic 8 – Artificial Intelligence and Machine Learning for Microgrid Applications

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Disclaimer

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List of Acronyms

ADMS	Advanced Distribution Management System
AI	Artificial Intelligence
AMI	Advanced Metering Infrastructure
ANL	Argonne National Laboratory
BTM	Behind-the-Meter
CHP	Combined Heat and Power
CNN	Convolutional Neural Network
DOE	U.S. Department of Energy
EV	Electric Vehicle
FERC	Federal Energy Regulatory Commission
GAN	Generative Adversarial Network
GNN	Graph Neural Network
HVAC	Heating, Ventilation, and Air-Conditioning
IDS	Intrusion Detection System
IEEE	Institute of Electrical and Electronics Engineers
INL	Idaho National Laboratory
ISO	Independent System Operator
LEL	Large Electric Loads
LLNL	Lawrence Livermore National Laboratory
LSTM	Long Short-Term Memory (recurrent neural network)
ML	Machine Learning
MPC	Model Predictive Control
μPMU	Micro-Phasor Measurement Unit
NERC	North American Electric Reliability Corporation

NILM	Non-Intrusive Load Monitoring
OE	(U.S. DOE) Office of Electricity
ORNL	Oak Ridge National Laboratory
PMU	Phasor Measurement Unit
PCC	Point of Common Coupling
RD&D	Research, Development, and Deployment
RL	Reinforcement Learning
RTO	Regional Transmission Organization
SCADA	Supervisory Control and Data Acquisition
SMR	Small Modular (Nuclear) Reactor
SNL	Sandia National Laboratories
T&D	Transmission and Distribution
TA	Technical Assistance
V&V	Verification and Validation
WLS	Weighted Least Squares

Executive Summary

The U.S. electric grid faces unprecedented challenges and opportunities, driven by increasing demands for reliability, resilience, and the integration of diverse energy resources. Artificial Intelligence and Machine Learning (AI/ML) are not merely incremental improvements but foundational technologies poised to revolutionize how microgrids operate, scale, and contribute to national energy objectives over the next 5 to 10 years. This strategic document articulates how advanced AI/ML capabilities, from algorithm breakthroughs to specialized edge inference chips, are essential for transforming theoretical advancements into real-world, scalable solutions that address critical Department of Energy (DOE) priorities.

The Imperative of AI/ML for Future Grid Resilience and Reliability

Microgrids, defined by the DOE as controllable entities capable of operating connected to or isolated from the main grid, are central to modernizing the electric infrastructure. They provide crucial resilience by autonomously powering critical loads, such as data centers, hospitals, and military installations during outages. AI/ML significantly amplifies this capability by enabling sophisticated forecasting, optimized operational control, and proactive anomaly detection, which are beyond the scope of traditional grid management systems. The rapid growth of AI/ML since 2020, fueled by advancements in transformer architectures, edge computing, and ubiquitous sensors, has now reached a maturity level where it can profoundly impact the power sector, particularly in distribution systems and microgrids.

AI/ML to Support Microgrids: Orchestrating a Complex Energy Ecosystem

AI/ML transforms microgrids from isolated islands of resilience into intelligent, flexible components of a dynamic, adaptable grid. The sheer complexity of coordinating diverse energy sources, including distributed generation, storage, and adaptable loads within a microgrid, and especially across networked microgrids, far exceeds the capacity of 20th-century control methods. AI-based algorithms are indispensable for:

- **Optimized Resource Coordination:** Dynamically managing heterogeneous resources (e.g., natural gas CHP, SMRs, geothermal, fuel cells, storage) to deliver dependable power at reduced cost while increasing resilience.
- **Networked Microgrid Orchestration:** Balancing consumer needs within individual microgrids against the broader objectives of the interconnected grid. AI/ML serves as a crucial tool for orchestrating myriad devices within and across these networked systems, enabling more distributed operations and control structures that enhance overall grid reliability and resilience.
- **Abnormal Condition Management:** Helping microgrids coordinate disparate generation resources during grid faults, cyber-attacks, or extreme weather events, ensuring continuity of critical services.

Microgrids to Support AI/ML Infrastructure: Powering the Digital Revolution

As AI's societal demand escalates, the infrastructure supporting it primarily data centers requires exceptionally reliable and robust power. Microgrids are in a unique position to meet this demand, which is projected to increase by as much as 65 GW in the U.S. by 2029. Data centers critically depend on uninterrupted power, where even minor flickers can cause significant downtime. Microgrids, with their ability to provide seamless transitions between grid-connected and islanded operations, offer the enhanced flexibility and redundancy necessary to:

- **Ensure Uptime:** Safeguard data centers against power disturbances, maintaining consistent uptime and operational stability.
- **Facilitate Integration:** Enable the integration of batteries, diesel generation, SMRs, and other backup power assets, allowing data centers to operate independently when the bulk grid experiences stress.
- **Address Capacity Gaps:** Provide power to locations where existing grid infrastructure may lack the capacity, promoting strategic siting of critical AI facilities.

Bridging Critical R&D Gaps: The DOE's Strategic Vision for AI/ML in Microgrids

This strategic document outlines critical research and development (R&D) gaps and opportunities. The DOE’s vision for the next 5-10 years centers on leveraging AI/ML to advance national grid objectives: enhancing reliability, resilience, affordability, and security through microgrid applications. This involves a strategic blueprint to guide DOE’s R&D investments, industry collaborations, and implementation decisions, focusing on moving National Lab-level systems to real-world scalability.

Foundational Development Areas and Challenges – "So What?" for Scalability & Adoption

Accelerating the adoption of AI/ML in microgrids requires addressing several foundational challenges, ensuring capabilities that meet current and upcoming needs identified by the DOE:

1. **Data Infrastructure, Edge-AI Hardware & Scalable MLOps Pipeline:** Widespread AI deployment necessitates robust infrastructure for data preprocessing, automated model training, validation, and performance monitoring. This includes supporting varying model complexities, ensuring compatibility across platforms (AWS, Azure), and developing efficient edge-compute solutions for remote microgrids. Scalability analysis is critical here, moving from lab environments to real-world, secure data pipelines with minimal lag, especially for real-time prediction and control.

2. **Secure & Interoperable Communications:**
   AI/ML applications in microgrids demand secure, reliable, and interoperable communication methods. This ensures data integrity, prevents tampering, and allows diverse devices from multiple vendors to communicate seamlessly. Standards-based communication promotes modularity, reduces vendor lock-in, and drives down costs, making AI-enhanced solutions more broadly deployable and accelerating their adoption across various microgrid types.
3. **High-Fidelity Digital Twins & Simulation Platforms:**
   As microgrids integrate more grid-forming generation, flexible loads, and data centers, traditional simulation tools become inadequate. AI tools are essential to speed up complex sub-second simulations and approximate microgrid physics. More importantly, digital twins provide a safe, high-fidelity environment for training AI algorithms (e.g., reinforcement learning) without risking critical infrastructure. This allows for rigorous testing, exploration of microgrid performance and microgrid controller performance. Digital twins and simulation platforms can serve a dual purpose of at ease operator training and workforce development.

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1 Introduction – Why AI-Enabled Microgrids Are Foundational to the Future U.S. Grid

1.1 Microgrids: Definition, Role in Grid Reliability & Resilience

Microgrids are a foundational concept in strengthening and modernizing the electric grid to support reliability, resilience, and energy abundance. The U.S. Department of Energy (DOE) defines a microgrid as a group of interconnected loads and generation resources within clearly defined electrical boundaries that acts as a single controllable entity relative to the bulk power system. In practice, a microgrid can operate connected to the main utility grid or switch to "island mode" during an outage to autonomously power local customers. This capability to isolate and self-sustain critical loads – such as data centers, hospitals, emergency services, defense installations and military bases, mining operations, and advanced domestic manufacturing facilities – is a primary driver for microgrid deployment to improve resilience, strengthen overall grid reliability, and support national security and economic competitiveness. By 2035, DOE envisions microgrids as essential building blocks of the future electricity delivery system (DOE-OE n.d.), supporting a grid that is more reliable, resilient, and better able to withstand disruptions while mitigating unnecessary cost transfers to ratepayers and advancing national economic and security priorities.

1.1.1 Role in Reliability and Resilience

Microgrids play a critical role in enhancing grid reliability and resilience. As cohesive, locally controlled systems, they can provide reliability services under normal, abnormal, and faulted conditions in ways that traditional, purely centralized architectures struggle to achieve. They can strengthen grid resilience by continuing to operate when the main grid goes down, supplying electricity locally during outages and speeding up recovery once service is restored. In grid-connected mode, microgrids can also provide dispatchable support to the surrounding distribution system, such as voltage support, local contingency reserves, and black-start capabilities for nearby feeders. For example, a microgrid serving a hospital, emergency response center, data center, or military base can isolate from a failing grid and keep critical services powered – a key benefit for critical infrastructure resilience. In day-to-day operation, microgrids improve reliability by handling local disturbances (voltage fluctuations, equipment failures) internally and reducing the load on distant transmission lines. This local management reduces the need for more expensive upstream reinforcements, helping to avoid unnecessary cost transfers to ratepayers. They also help mitigate wider grid disturbances by functioning as grid resources for faster system response and recovery. In essence, microgrids add a layer of defense against outages: if one part of the grid fails, microgrids can keep the lights on in their corner of the network.

Microgrids have comparatively simple interconnection process that can lead to fast interconnection times for large electric loads such as data centers that require high-availability power. When used to integrate these large loads, microgrids can reduce or defer costly transmission and sub-transmission upgrades, providing a more targeted, modular solution that both supports bulk-system reliability and helps manage overall cost impacts on ratepayers.

Grid-connected microgrids can also provide reliability services under normal conditions, not just during outages. Utility-owned or jointly owned microgrids can be designed from the outset to satisfy interconnection and protection requirements while still providing firm, high-availability power to large electric loads such as data centers, advanced domestic manufacturing facilities, and defense installations. By locating controllable local energy supply and demand resources closer to these loads, microgrids can reduce the need for costly transmission and substation upgrades, helping to mitigate unnecessary cost transfers to ratepayers. In this way, microgrids offer a cohesive solution for delivering reliability and resilience services under normal, abnormal, and fault conditions, while supporting national economic and security priorities.

1.2 Rapid Growth of AI/ML Capabilities Relevant to Power Systems

Since 2020, explosive progress in AI/ML, driven by transformer architectures, edge inference chips, and ubiquitous sensors, has reached the power sector particularly in distribution systems and microgrids. Breakthroughs in algorithms, substantial growth in computing power, and an explosion of data from distributed sensors have made AI/ML increasingly practical and effective for grid operations. Modern computing hardware, such as specialized edge processors (e.g., NVIDIA Jetson Orin, Intel Movidius), allows sophisticated AI/ML models to operate efficiently in real-time at the grid edge, critical for rapid grid decision-making.

AI/ML applications now greatly enhance forecasting accuracy, operational control, and optimization capabilities. In the context of microgrids, these capabilities translate directly into more reliable scheduling of local resources, improved coordination with the host utility system, and better use of flexible loads and storage to avoid unnecessary capital investments. Advanced machine learning algorithms significantly enhance load and event forecasting accuracy, providing grid operators clearer insights into future grid conditions. Self-learning controllers dynamically manage loads, storage, and generation resources in real-time, optimizing system performance and maintaining stability. Additionally, AI-driven tools rapidly detect anomalies and equipment faults, allowing proactive interventions to prevent outages and reduce system downtime. For microgrids and networked microgrids, these same capabilities help ensure that high-availability customers remain served during disturbances while still supporting system protection and safety objectives. These rapid advancements position AI/ML as an essential operational asset, driving substantial gains in efficiency, affordability, and resilience within microgrid and distribution system operations.

1.3 AI/ML to Support Microgrids

Energy Addition, Not Subtraction, requires the incorporation and orchestration of a diverse set of energy sources —including distributed generation assets like natural gas-powered combined heat and power (CHP) systems, small nuclear reactors (SMRs and Microreactors), geothermal energy, and fuel cells (Prabakar et al. 2022)—along with energy storage and adaptable loads. Microgrids are a key enabling technology which can simplify the management of the power system by breaking it into more manageable pieces which can be optimized to deliver power at reduced cost to consumers while increasing resiliency and making the delivery of power more reliable. Within a given microgrid, the process of coordinating a large set of heterogeneous resources for these objectives challenges the capabilities of 20th century methods of control and optimization. AI-based algorithms for microgrid control and coordination will be needed to cheaply and efficiently deliver dependable power to essential systems, such as data centers, advanced manufacturing, and military installations, which are crucial for national security and economic well-being.

The orchestration of microgrids themselves (i.e., networked microgrids) is also a highly non-trivial task which will need to balance the needs of consumers and devices within the component microgrids against the larger objective for which the microgrids are being coordinated. In this way, microgrids can act as foundational elements for the larger grid, enabling more distributed operations and control structures that improve the grid's overall reliability and resilience. Enabling this future is no small task, however, as the complexity of coordinating new types of microgrid components, such as grid forming controllers, is difficult even for a single microgrid. As microgrids become increasingly networked to support critical grid functions, AI is envisioned to be a crucial tool capable of orchestrating a myriad of individual devices within and across microgrids.

1.4 Microgrids to Support AI/ML Infrastructure

Driven by increased societal demand for AI itself, microgrids will be in a key position to support the exponential growth of data centers which is presently underway. A 2025 study from researchers at Duke University claims that data centers are expected to account for an increase of as much as 65 GW of electric power demand in the US by 2029 (Norris 2025). Data centers require exceptionally high reliability in electrical service due to the power electronics where even minor power flickers can result in significant downtime. To achieve this level of reliability, data centers commonly deploy microgrids and uninterruptible power supply (UPS) systems for seamless transitions between grid-connected and islanded operation during outages or any power quality event. As the existing power grid infrastructure, in many areas, does not have the capacity to supply electricity to locations where it may be desirable to locate a datacenter, the enhanced flexibility provided by microgrids could allow data centers to operate independently from the bulk power grid during certain periods of operation, as well as facilitate the integration of batteries, diesel generation, SMRs and other generation assets capable of providing backup power during grid failures or extreme weather (Vaidhynathan et al. 2025). Microgrids create a robust, redundant electrical system that safeguards data centers against power disturbances, maintaining consistent uptime and operational stability.

1.5 Summary of Critical R&D Gaps and Opportunities

This strategic plan is consistent with the U.S. Department of Energy's (DOE) broader effort to outline how Artificial Intelligence and Machine Learning (AI/ML) can advance national grid objectives, specifically enhancing reliability, resilience, affordability, and security through microgrid applications.

The strategic plan provides DOE leadership, program managers, utilities, policymakers, and technical stakeholders with a clear strategic perspective on AI/ML's potential within microgrids. It articulates the practical ways AI/ML can solve critical grid challenges—such as ensuring continuous power during outages, optimizing operational costs, and safeguarding against cyber threats. This plan does not aim to provide exhaustive technical details or specific policy guidance; instead, it serves as a strategic blueprint to guide DOE's R&D investments, industry collaborations, and implementation decisions. The insights and recommendations presented here support DOE's overarching goals for a secure, reliable, abundant, and resilient national electric grid.

2 Vision for the Future and Key Microgrid Needs pressable by AI/ML

2.1 Complexity of Future Microgrid Control

2.1.1 Networked and Nested Microgrids

In order to *Advance Energy Addition, Not Subtraction*, future power systems will feature a diverse set of loads and generation sources which will need to be properly managed to *Promote Affordability* and *Strengthen Grid Reliability and Security*. Proper management of these assets at scale will require the composition of many interacting microgrids, leading to new levels of operational complexity. Networked (or nested) microgrids refer to multiple microgrids linked on the same utility circuit, coordinating over a wide area as an integrated system (Schneider Electric n.d.). By networking microgrids in this way, generation and load assets can be scaled to support the larger grid (in addition to serving local demand), effectively using microgrids as building blocks of a more distributed and resilient overall grid (Donde et al. 2022). This paradigm shift toward many small, networked grid elements challenges the traditionally centralized control approach. Additional layers of hierarchical or peer-to-peer control are required to manage interactions between microgrids, introducing unique complexity. AI-based techniques are well suited to handle this complexity: they can act as high-level microgrid coordinators and assist human operators by sifting through an overwhelming number of control options and predicting the outcomes of different decisions.

2.1.2 Grid-forming Inverter and Large Load Coordination

As new types of generation sources, power-electronic converters, and control approaches are integrated into the power system, the behavior of the grid is becoming less predictable. This challenges many conventionally held paradigms of how grid operators manage their systems. For example, many inverter-based resources are now operated in grid-forming mode (actively regulating local voltage and frequency), which makes it challenging to coordinate them alongside conventional synchronous generators and large data centers to maintain stable system frequency and voltage.

In order to advance *Energy Addition, Not Subtraction,* if will be necessary to calibrate the control loops of grid-forming assets, conventional generators, and large dynamic loads in order to avoid undesirable grid behaviors such as wide area frequency and voltage oscillations (Ko et. al. 2025). Microgrids can provide a scalable structure for breaking the calibration process into smaller pieces, which can be optimized individually and coordinated to ensure proper behavior in large networks with many hundreds and thousands of devices. AI tools will be needed to: 1) properly simulate dynamic microgrid behavior, and 2) optimize over these simulations to properly calibrate grid-forming inverters and load loads in a variety of different operational scenarios (i.e. during faults or extreme weather). Ensuring critical generation and load assets are calibrated properly during contingencies will substantially *Strengthen Grid Reliability and Security*.

2.2 Reliability and Resiliency Objectives

2.2.1 Managing All Generation Types and System Configurations

While the exact composition of the future electric grid is unknown, *Energy Addition, Not Subtraction,* will require the integration of a heterogenous set of both generation and load assets. These devices will need to be properly coordinated to enhance reliability, power quality, affordability, operability, and safety, while also supporting energy independence. Microgrids, specifically, are expected to play a large role in promoting grid reliability. Through intelligent integration of a diverse set of generation sources, such as natural gas-fired combined heat and power (CHP), small modular reactors (SMRs), geothermal, fuel cells, storage, and dynamic loads, microgrids will enable a more flexible electric power system more broadly. The ability to isolate either themselves or a problematic portion of the electric grid[1] will ameliorate consequences stemming from faults, cyber-physical attacks, and other disturbances. The process of determining when and how to isolate portions of a large power system can be cast through the lens of networked microgrids enabled through AI algorithms trained to maximize the delivery of electricity under varying network topologies.

2.2.2 Handling Disturbances, Faults, and Cyber-physical Attacks

Coordination of a heterogeneous set of generation resources under abnormal grid conditions (such as grid faults or cyber-attacks), presents several challenges which are ideally addressable with AI-enabled microgrids. Complex disturbances in large networks with thousands of controllable generators and loads can unfold in ways that are difficult for human operators to predict or manage with pre-programmed rules alone. Networked microgrids provide a tractable and scalable way to simulate and control subsets of devices for a system-level objective. Here, AI techniques offer two key advantages: enhanced simulation for planning and improved real-time decision-making for control. For instance, generative AI models can be used to generate a myriad of realistic disturbance scenarios (e.g. various fault conditions, extreme weather events, or coordinated cyber-attacks) and predict their outcomes, enabling operators to explore "what-if" situations in advance. This helps in stress-testing microgrid preparedness and training operators on rare events. Meanwhile, reinforcement learning (RL) is a natural choice to develop robust control policies for a diverse set of microgrid components during abnormal conditions. RL-based controllers learn optimal responses by interacting with simulated microgrid environments and can discover control strategies that maintain stability and service continuity during faults or attacks. For example, an RL algorithm could learn how to shed loads, re-dispatch generation, or reconfigure network topology in response to a major disturbance, improving the microgrid's self-healing and recovery capabilities. Overall, AI/ML techniques provide a toolkit for both anticipating disruptive events (via data-driven simulations) and autonomously managing the microgrid when such events occur, thereby greatly *Strengthening Grid Reliability and Security* under adverse conditions.

[1] In the case the microgrids are networked

2.3 High-Level Goals & Success Metrics

Microgrids will be a key enabling technology of the power grid of the future, specifically facilitating: 1) Reliability and Resilience, 2) Security, 3) Energy Abundance Through Addition, and 4) Affordability and Economic Advancement. AI is a tool which is envisioned to underpin all these pillars.

To support grid reliability and resilience, AI can enable the development of advanced forms of microgrid control, allowing microgrids to adapt to both external and internal dynamic operation conditions such as communications disruptions, component failures, and the behavior of neighboring systems. AI solutions will also allow the creation of networked microgrids with dynamic boundaries, promoting resiliency to extreme weather and other events. Grid security will be facilitated by the use of AI approaches to create control and communication schemes which are robust to adversarial attacks. The use of AI to coordinate, control, and monitor a diverse set of distributed energy assets will increase grid hosting capacities and allow for dynamic reconfiguration[2] of assets, thereby enable energy abundance through addition. AI algorithms will also support increased affordability and economic advancement through better techniques to optimize the microgrid. Utilizing microgrid solutions as non-wires alternatives can improve utilities' grid cost management and investment strategies, thereby ameliorating costs which may otherwise have been passed onto consumers.

Success metrics for AI-enhanced microgrids will therefore span technical, economic, and reliability criteria. Some key metrics include reductions of microgrid capital costs and commissioning times, improved reliability indices (fewer/shorter outages and better power quality), increased hosting of flexible loads and distributed energy assets, faster simulation and co-simulations, improved state estimation accuracy and control response times, and better power quality. AI-driven technologies to enable advances in microgrids will further cement the US as a leader in in resilient and smart microgrid technologies worldwide.

[2] In response to changes in seasons or daily/weekly load patterns

3 Foundational Development Areas and Challenges

3.1 Data Infrastructure, Edge-AI Hardware & Scalable MLOps Pipeline

Widespread deployment of AI will necessitate the presence of an infrastructure that supports varying levels of AI model complexity. This infrastructure must enable preprocessing and integration of potentially large and heterogeneous data sources, automate model training and retraining, and enable model validation and model testing for benchmark performance, and monitoring model performance. Compatibility across multiple online data and Machine Learning Operations (MLOps) platforms (e.g., AWS, Azure, etc.) will be necessary to ensure computing and hardware capabilities, and data availability, match the requirements for various microgrid applications. It is expected that this infrastructure will likely be tasked with facilitating time-based synchronization of data, computing derivative metrics from sensor data (e.g., phasor measurements), and storing and updating many (sometimes billions) of numerical parameters for ML models. Additional considerations for microgrids necessitate that data is secured and that appropriate guardrails exist within the data pipeline and ML models to prevent unintended release of sensitive data.

As microgrids offer the ability for remote areas to support power generation, when ML becomes an integral part of that, we must also consider ML local support tools and devices that won't have the benefit of regular and reliable online platforms (AWS offerings). In these environments, smaller models and more efficient computing hardware are necessary, however they must still maintain an acceptable level of performance. This is not just an engineering effort for designing and working with smaller, more powerful processing units and expanding network coverage. It also includes enhancing the security of data and performing analytics locally.

For accessibility and privacy reasons, many microgrid architectures may favor edge-compute over more cloud-oriented infrastructure. As such, it will be necessary for edge-capable models and hardware to maintain acceptable levels of performance and security without the benefit of real-time infrastructure support and resources. Furthermore, applications related to real-time microgrid prediction and control will require data structures that are ready-accessible and frequently updated, data processing pipelines with minimal lag, and the ability to real-time combine sources for ingest by algorithms.

3.2 Secure & Interoperable Communications

The AI/ML applications can be housed in a central computing facility (e.g., cloud-based), or they can be located on the edge devices. Regardless, they will likely need to receive information from external sources, and thus need to communicate with other devices. Like traditional control methods, AI/ML-based controls and analysis need to know not only that the data is valid and can be trusted, but also understand how to communicate with a variety of sources. Secure, reliable, and interoperable communications methods are required to ensure the best performance of the AI/ML-based applications.

Secure communications are obviously needed to ensure the information being received has not been tampered with, and that any controls or outputs from the AI/ML application reach their destination without any alterations. AI/ML applications are not necessarily unique in this requirement, but may be incorporating more diverse, more numerous, and faster updating data streams than traditional controls. Improving the trust/integrity of the data streams will enable the AI/ML applications to focus on their primary objective.

Interoperability will be needed for two reasons:

1) Ensuring applications can communicate with the largest number of potential devices on the microgrid as possible, maximizing the capabilities and impacts on the system.
2) Fostering a competitive environment where devices from different vendors can provide different functions, which limits vendor lock-in and closed-form proprietary protocols. This also enables modularity in the microgrid enabling faster/easier deployment of the AI/ML application.

With standards-based communications and data schemas to promote interoperability, equipment deployment and replacing aging/failing devices can occur more readily, helping to drive down the costs of overall microgrid while deploying the AI/ML-enhanced solutions. This helps ensure the AI/ML-based microgrid controls can continue to promote a reliable, resilient, and secure contribution to power systems.

3.3 High-Fidelity Digital Twins & Simulation Platforms

A key element needed to *Unleash American Energy Innovation* will be the availability of high-quality simulation platforms and digital twins. As microgrids continue to host increasing amounts of grid-forming generation, flexible loads, data centers, and electric vehicles, many traditional assumptions on which existing simulation tools were built are becoming increasingly invalid. Sub-second simulations of relatively small networks (approx. 30 buses) can contain over 700 states (Bossart et. al. 2025). As the networks being studied grow in size, it may take several hours of computation time to simulate a few seconds of microgrid behavior. AI tools could be leveraged to try and speed up the simulation process via approximating portions of microgrid physics which are difficult to handle numerically.

In addition to increasing microgrid simulation capabilities, AI has a vast array of uses for microgrids, including planning, protection, and control. However, for many applications involving critical infrastructure, including microgrids, AI algorithm training cannot (or should not) be conducted on “live” (i.e. customer-serving) power networks. Many algorithms, such as reinforcement learning, are encouraged to act randomly during the training process, which can lead the agent to make new discoveries in learning how to solve the task at hand. The flip-side of this coin is that sometimes the agent will make a terrible decision, which, though valuable for the learning process, could have economic or safety ramifications. This concept of exploration vs. exploitation could alternatively be conducted in a simulation or digital twin of the microgrid. However, in order to ensure the AI agent learns the right lessons, the simulator needs to represent the aspects of the microgrid which are pertinent to the task at hand.

Furthermore, once a high-fidelity, validated digital twin is established, AI/ML techniques can be powerfully applied for scalability analysis of various systems within a microgrid, enabling both scale-up and scale-down scenarios. This capability allows for the at-scale validation of system designs, particularly valuable within national laboratories. It facilitates the characterization of a validated system at one scale and its subsequent analytical scaling to meet diverse operational needs, especially beneficial for large-scale deployments where empirical characterization would otherwise be prohibitively expensive.

3.4 Explainability, Verification & Certification Frameworks

As AI/ML algorithms increasingly support microgrid operations, ensuring these models are transparent, trustworthy, and certifiable becomes essential for maintaining grid reliability and safety. Without trust in AI outputs, utilities will be reluctant to adopt this emerging technology. Explainable AI (XAI) helps bridge this trust gap by providing clarity on how models reach their decisions. This transparency is particularly critical for grid operators and regulators who rely on AI tools in mission-critical areas such as protection and control. Traditional "black-box" models (e.g. deep neural networks) can offer impressive performance but lack interpretability, raising concerns about accountability and validation. Indeed, various XAI methods are emerging to tackle this transparency issue, recognizing that the potential benefits of AI for microgrid efficiency and reliability are significant (Ayub, Quevedo, and Sandberg 2025).

Robust verification and validation (V&V) frameworks are needed to systematically test AI/ML models under a range of operational scenarios, including edge cases and faults. These frameworks should assess performance metrics such as accuracy, decision latency, and robustness, while also incorporating uncertainty quantification to inform human decision-makers. Moreover, recent studies highlight that challenges like model interpretability, data quality, and regulatory standardization must be addressed to realize AI's advantages in energy systems. Finally, a path toward certification must be defined to enable widespread deployment of AI in microgrids to comply with utility commissioning practices and compliance with regulatory requirements. Establishing explainability, rigorous V&V, and certification processes are prerequisites for utility trust, market adoption, and regulatory approval of AI-enabled microgrid technologies. By building this foundation, the industry can ensure that AI/ML tools genuinely bolster grid reliability, resiliency, and security rather than introduce new risks.

3.5 Operator Readiness – Training, Roles and Responsibilities, and Human Factors

Microgrid operators perform a critical role in maintaining grid resilience by anticipating disruptions and adapting their decisions in response to changing or ambiguous information. AI/ML tools can support operators by performing a variety of tasks to help operate microgrids including energy and demand forecasting, anomaly detection and real-time control of the microgrid. Microgrid operator roles and responsibilities must evolve with the integration and proliferation of these tools requiring new training and standard operating procedures (Curtis et. Al. 2025). Without thoughtful changes to work processes, and proper training, operators may fail to adopt or misuse these tools (e.g., over reliance on AI/ML decisions and recommendations) and tool performance may suffer. Failing to prepare operators for the introduction of AI/ML jeopardizes the operators' ability to help maintain grid resilience.

It is important to note that microgrid operators are not being replaced by AI/ML, but their introduction presents a challenge by changing and possibly expanding operators' roles and responsibilities. For example, operators may take on greater monitoring responsibilities that require validating AI decisions and overriding when necessary. This real-time performance monitoring will require operators to not only maintain their knowledge and skills for managing the grid but also learn the nuances and performance limitations of the AI/ML tool. The ability to diagnose and predict AI/ML errors will be a required skill for operator readiness. Another challenge may be the introduction of tasks required for managing AI/ML model performance. Some AI/ML tools may require operators to provide corrective feedback to teach their models. If operator corrective feedback is required, this new task must be properly integrated into existing operator workflows, documented in standard operating procedures and incorporated into operator training programs. Developers and human factors practitioners must prepare operators for the new tasks required to operate and manage AI/ML. By prioritizing operational readiness through training and well defined roles, responsibilities and procedures, organizations can safeguard grid resilience even as technology evolves.

4 Technical Areas for Continued Advancement

4.1 AI/ML in Microgrids for Forecasting and Scheduling

Emerging microgrids harbor a diverse mix of power generation and storage technologies that serve critical infrastructure, large flexible loads, and commercial centers alike. To ensure energy efficiency, resilience, and affordability, microgrid operators must be able to reliably forecast generation and demand over a horizon of few hours up to a day. This enables operators to optimize and decide how to schedule available generation and storage to meet anticipated demand. It also drives crucial financial decisions that may entail trading energy with adjacent microgrids or the grid, expanding or shrinking control boundaries, or participating in the electric utility's flexibility programs to meet economic or resilient objectives (Starke et al. 2025).

The problem of forecasting could be solved either by a physics-based numerical solution or a data-driven machine learning (ML) model. While physics-based solutions require accurate representations of the underlying electrical model of the generation and demand resource, a data-driven model approximates the nonlinear relationship between a set of fairly independent factors (e.g., features such as temperature, time-of-day, day-of-week, holidays and other seasonalities to the historical patterns impact demand) and the dependent variable of interest (e.g., timeseries demand). The models could be supervised such as decision trees or neural networks (Sundararajan et al. 2023), or semi-supervised such as reinforcement learning (Aslam et al. 2025). Physics-based models could be combined with learning models to create physics-informed ML techniques (Meng et al. 2025). Black-box estimation of the generation or demand resource could also yield approximations of future energy patterns (Colón et al. 2024). It is to be noted that estimation and forecasting are not interchangeable terms. Estimations approximate the target based on the available data and either model the present or the past behavior of the system. Forecasting, however, attempts to model the system's future behavior based on the available present and past data.

4.2 AI/ML in Microgrids for Real-Time Visibility and State Estimation

Microgrids require accurate, real-time visibility of internal states to operate reliably and safely, particularly under dynamic conditions with high penetration of flexible loads and microgrid-integrated local energy supply and demand resources. Real-time visibility underpins the ability of microgrids to support enhanced grid reliability and resilience while mitigating unnecessary cost transfers to ratepayers. Traditional model-based estimators (e.g., weighted least squares or WLS) often struggle with low observability and fast-changing load or generation profiles; for example, a WLS state estimator may fail to converge or lose accuracy when the system equations become ill-conditioned (Rana and Li 2015). Such loss of visibility can limit a microgrid's ability to support reliable operations for both the microgrid and the surrounding grid. AI/ML approaches offer a complementary path leveraging existing AI/ML methods to learn latent system behavior from multi-scale sensor data like Phasor Measurement Units (PMUs), Advanced Metering Infrastructure (AMI) smart meters, SCADA systems, power quality (PQ) meters and grid edge intelligent controller feeds. By recognizing subtle patterns in this data stream, machine learning can fill in information gaps that conventional methods miss, thus improving situational awareness and supporting reliable and secure microgrid operations. For microgrids that serve large electric loads such as data centers, advanced domestic manufacturing, or defense installations, this real-time visibility is critical to ensure they strengthen, rather than destabilize, the surrounding grid and help mitigate cost transfers to ratepayers.

Techniques such as neural networks (including physics-informed and graph-based models) and ensemble learning can infer voltages, power flows, and device states with low latency, even when sensor coverage is sparse or noisy. When integrated with high-fidelity digital twins, these models can track system states during faults, topology reconfigurations, or cyberattacks, enabling proactive mitigation and faster recovery (a key aspect of resilience and reliability for both the microgrid and the wider grid it supports) (Londagin 2025). Importantly, these algorithms must be designed with built-in uncertainty quantification and explainability so that operators trust their outputs and regulators approve their use. Real-time state estimation is a foundational capability that supports subsequent functions such as protection, dispatch, and optimization. When these downstream functions are informed by accurate, AI-enabled visibility, microgrids are better able to maintain service to critical loads during disturbances, reduce the need for costly over-design, and support the broader grid as dependable, modular building blocks. These functions, in turn, help ensure reliable, resilient, and efficient microgrid operations while creating clear pathways to higher technology readiness levels and eventual handoff of mature solutions to industry.

4.3 AI/ML in Microgrids for Incipient Failure and Anomaly Detection and Predictive Maintenance

Grid reliability can be improved by correcting issues before they become catastrophic, which directly aligns with AI's strengths in anomaly detection and forecasting. Microgrids face significant challenges in detecting incipient equipment failures due to the complexity of the changing system topology and the diversity of their components. Traditional detection methods rely on scheduled inspections, generic threshold-based alarms, or just waiting until something fails. Relying on routine or reactive procedures can lead to critical faults, system downtime, or reduced reliability.

AI-driven anomaly detection techniques can identify subtle deviations from normal behavior, allowing for early detection of potential issues for maintenance or replacement before failure. This decreases the number of outages and allows for microgrid operators to schedule maintenance proactively. For example, long short-term memory (LSTM) and recurrent neural networks excel at modeling sequential operational data from voltage, current, frequency, and temperature to capture temporal trends, such as lithium-ion battery degradation. Autoencoders can learn normal operating patterns to flag incipient faults from a failing lightning arrestor or partial vegetation contact. These AI-driven methodologies enhance early-stage detection, allowing microgrid operators to transition toward predictive and condition-based maintenance.

4.4 AI/ML in Microgrids for Protection – Fault Clearing and Self-Healing Systems

Microgrid protection continues to be a difficult challenge for microgrid developers due to the wide range of fault current magnitudes and directions between different operating modes. The bidirectional power flows, intermittent generation patterns, and variable load conditions in microgrids complicate accurate fault detection, making traditional protective schemes less effective. Accurately isolating faults requires highly selective and coordinated protective devices, which is a slow and cumbersome task for protection engineers to develop using electromagnetic transient (EMT) simulations. AI has the potential to alleviate this burden for protection engineers by either intelligently determining the protection settings or doing a purely AI-based protection solution.

AI can significantly enhance fault clearing in microgrids by improving the accuracy, sensitivity, selectivity, coordination, reliability, and speed of fault detection and isolation processes. Using conventional relays, AI can be used to optimize the protection settings for normal operation or in a real-time adaptive framework. The development of these advanced AI-based protection schemes critically relies on realistic training environments. Integrating Electromagnetic Transients (EMT) modeling is essential as it creates high-fidelity, real-world emulation scenarios that encompass actual fault events and rare occurrences. This allows AI/ML learning algorithms to be rigorously trained for robust fault identification and rapid, appropriate responses. Furthermore, such an environment is indispensable for establishing AI-based dynamic protection and recovery systems, which can overcome the limitations of today's predominantly static protection settings. This capability enables the development of truly dynamic protection setting adjustments, significantly enhancing grid resilience and operational flexibility. AI-based protection schemes using algorithms such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), support vector machines (SVMs), and ensemble decision-tree methods, can detect faults and determine their location to swiftly identify the correct breakers to open. Both solutions can continuously learn as the future grid changes to adjust protection settings and optimize coordination among protective devices.

Finally, AI enables microgrids to become self-healing through automated network reconfiguration, adaptive protection schemes, and intelligent control actions. Microgrids equipped with AI-driven self-healing capabilities can rapidly isolate faulted sections, intelligently reroute power flows, and quickly restore supply to healthy network areas, dramatically improving system resilience and reducing downtime.

4.5 AI/ML for Microgrid Planning and Siting

Planning and siting of microgrids traditionally rely on deterministic models and rule-of-thumb heuristics, which often fail to capture the complexity of future energy needs, evolving grid constraints, resilience considerations, and cost impacts on different customer classes. AI/ML offers the ability to enhance microgrid planning by learning from large, diverse datasets – geospatial load patterns, outage histories, availability and characteristics of local energy supply and demand resources, infrastructure limits, and critical service requirements for facilities such as data centers, advanced manufacturing sites, and defense installations – thereby providing more realistic scenario analysis than conventional tools. By uncovering patterns in this data, AI can help planners identify opportunities and risks that would otherwise be overlooked, more effectively targeting microgrid solutions that enhance reliability and resilience while mitigating unnecessary cost transfers to ratepayers, improving long-term preparedness.

Supervised learning and reinforcement learning models can identify high-impact locations for microgrid deployment based on metrics like resilience value (e.g., mitigating outages for critical facilities and improving local reliability), congestion relief, or cost-effectiveness. In parallel, unsupervised clustering and dimensionality reduction techniques help planners visualize and make sense of large-scale data, discovering hidden correlations that inform more robust and secure solutions. By combining these methods with multi-objective optimization, AI/ML enables more adaptive and holistic siting decisions that balance efficiency, resilience, affordability, and economic advancement goals. For example, an AI-assisted tool might simultaneously consider reliability improvements, economic returns, and the ability of microgrids to support large electric loads without creating new system instabilities or undue cost burdens when evaluating microgrid proposals. Integrating these advanced tools into existing utility planning workflows will require standard data interfaces and transparent, explainable outputs to ensure decision-makers understand the rationale for proposed microgrid investments. Ultimately, AI-informed planning can better target investments to strengthen grid resilience and affordability, supporting DOE's objectives of a more reliable, secure, and future-ready grid and creating a clearer pathway for maturing planning and siting tools from early-stage research through field validation and eventual handoff to industry.

4.6 AI/ML in Microgrids for Load Learning and Disaggregation

Understanding behind-the-meter consumption is essential for accurate load forecasting, optimal dispatch, and demand response; functions that ensure reliable and cost-effective microgrid operations and support broader grid reliability and resilience. Traditional load models often treat customer demand as an aggregate, inflexible block, masking the diversity and flexibility of modern end-uses. AI/ML-based load disaggregation (also known as non-intrusive load monitoring or NILM) can decompose a composite demand profile into individual device-level loads. NILM analyzes the electric signals from a single metering point and infers the activity of different devices, providing a low-cost alternative to installing sub-meters on every device (albeit with some privacy considerations). By leveraging high-resolution data from AMI smart meters or other sensors, machine learning models (e.g., convolutional and recurrent neural networks) can identify patterns unique to HVAC systems, as well as large process loads in advanced manufacturing or critical IT equipment in data centers.

Once disaggregated, these device-level profiles can be used to estimate flexible load capacity, predict demand spikes, and detect anomalous consumption that might affect power quality. For instance, an AI algorithm could learn the typical usage pattern of a water heater within the microgrid and anticipate when it can be briefly curtailed to smooth out a demand peak, improving overall efficiency while avoiding unnecessary investments that could otherwise increase costs for ratepayers over time. Load learning also enables microgrids to better coordinate with building energy management systems and adapt to user behavior, unlocking advanced demand response schemes that enhance microgrids' ability to support the surrounding grid during stressed conditions. This fine-grained visibility into consumption not only helps optimize microgrid economics (by reducing waste and targeting efficiency measures), but also supports reliability and resilience by identifying controllable loads that operators can shed or adjust during grid stress events, particularly in microgrids serving large electric loads such as data centers, advanced domestic manufacturing facilities, or defense installations. While promising, successful deployment of these techniques depends on access to sufficiently detailed (and labeled) datasets, robust privacy controls to protect consumer data, and real-time processing capability at the edge. Overcoming these challenges will allow load-disaggregation AI to play a key role in managing microgrids for affordability and reliability, accelerating the transition from early-stage research to field-validated solutions that can ultimately be transferred to industry as part of the future grid.

4.7 AI/ML in Microgrids for Control

AI/ML is increasingly being explored for adaptive microgrid control to complement and enhance traditional model-based techniques (like model predictive control) and thereby improve system flexibility and reliability. Approaches such as reinforcement learning (RL), imitation learning, and hybrid AI+physics methods enable the development of controllers that can adapt to changing system dynamics, load and generation asset configurations, and operational objectives (e.g., minimizing cost, or outage duration), all without requiring a perfect real-time model of the microgrid. Notably, AI-driven energy management systems have demonstrated both cost and resilience advantages over conventional controls. These learning-based controllers can continually refine their strategies based on feedback, becoming smarter and more effective over time.

In practice, AI-based controllers can support voltage and frequency regulation, generation dispatch, intelligent load behavior, and optimal grid islanding coordination under uncertainty. For example, a deep RL controller might learn to balance power flow among solar PV, battery storage, and flexible loads while accounting for forecast errors and grid constraints, thereby maintaining stability at lower cost than heuristic methods. Such adaptive controllers are especially valuable for grid-forming inverters (devices that establish a stable voltage/frequency reference in island mode), large data centers, or for rapid service restoration after outages. In fact, AI control schemes are key enablers of self-healing grid actions: they can autonomously isolate faults, reconfigure power flows, and restore service in real time through intelligent switching and local control – dramatically improving resiliency and minimizing outage impact. However, their safe deployment hinges on rigorous offline training, thorough testing, and the inclusion of explainability and fallback mechanisms to ensure they behave reliably in unanticipated scenarios. Techniques like "sandbox" simulations and digital twins are essential for validating these AI agents under myriad what-if conditions and for earning stakeholder confidence. Looking ahead, establishing verification and certification processes (as discussed in section 3.4) for AI controllers will be critical. With proper safeguards, AI/ML-driven control can greatly *Strengthen Grid Reliability and Security* (through faster and smarter response to disturbances) and *Promote Affordability and Consumer Choice* (through optimized resource utilization), thus preparing the grid for the challenges of tomorrow.

4.8 AI/ML for Microgrid and Networked Microgrid Cybersecurity

Cybersecurity of the electric power system is a critical and wide-ranging topic with a variety of stakeholders. Many offices within DOE have an explicit focus on cybersecurity[3], but microgrids and networked microgrids present unique challenges in this domain that intersect directly with reliability, resilience, national security, and affordability and are well suited to AI-enabled tools and methods (Hossain-McKenzie, 2020). These challenges are amplified for networked microgrids that coordinate across multiple feeders or sites, increasing the number of digital interfaces that must be monitored and protected.

As digitally controllable devices and microgrid-integrated energy supply and demand resources grow in both number and complexity, microgrids will need advanced monitoring, control, protection, and communication capabilities. These systems will need to be capable of increasing system observability and identifying attacks in their early stages so that microgrids can continue to support critical loads and strengthen, rather than weaken, overall grid reliability. Additionally, advanced AI tools could support operators in developing and executing mitigation strategies when an attack is detected. For example, AI algorithms could recommend targeted switching, reconfiguration, or load-shedding actions within a microgrid to isolate compromised components while maintaining service to priority loads and limiting cost and reliability impacts on customers. Such efforts are already being funded by CESER (Postelwait, 2024), but the additional level of control and coordination inherent within microgrids creates a need for dedicated research in this area that coordinates closely with broader DOE cybersecurity initiatives and emphasizes field validation and transition of successful approaches to industry.

Microgrid technology is significantly influenced by the supply chains that provide its various components and devices. Current analysis and planning tools do not adequately address the risks related to supply chains, such as cybersecurity threats and potential backlogs. Additionally, these tools often lack insight into the complete life cycle of microgrid technologies. To create microgrid systems that are both practical to deploy and secure, new tools are needed that take into account the limitations and risks associated with supply chain availability and security. For microgrids serving large electric loads such as data centers, advanced domestic manufacturing, and defense installations, proactively managing these risks is essential to support national security and energy dominance objectives. AI/ML tools could be leveraged to incorporate supply chain risk into the microgrid planning process, or to identify vulnerabilities in microgrid components via supply chain analysis, helping prioritize design choices and mitigation

[3] Most notably CESER, but other programs within OE and EERE also support work on cybersecurity.

measures that reduce the likelihood and impact of cyber-enabled disruptions over the full technology life cycle.

5 DOE Role in Research and Development

The U.S. Department of Energy's Office of Electricity (OE) plays a pivotal role in advancing AI/ML solutions for microgrids. that enhance grid reliability, resilience, and security while managing cost impacts on ratepayers. In FY2024, OE funded an Argonne-led project applying AI/ML for real-time microgrid visibility and data fusion – for example, developing new microgrid situational awareness using real-time sensor analytics in both microgrids and the surrounding distribution system. This exemplifies OE's focus on foundational, pre-commercial tools that improve microgrid visibility, adaptive control, protection, and fault response so that microgrids can better support grid reliability and resilience while mitigating unnecessary cost transfers to ratepayers. By investing early in such technologies, OE is bridging critical gaps between research prototypes and field-ready solutions and driving technologies toward mid-range technology readiness levels (around TRL 6) in the first five years, so that subsequent years can focus on larger-scale demonstrations, standards, and industry deployment, well before the private sector deems them commercially "safe" bets.

DOE's R&D priorities are closely aligned with national objectives of energy leadership and grid resilience. The agency remains "committed to restoring America's energy dominance." In practice, this means ensuring the U.S. leads in both AI innovation and reliable, resilient, and secure energy delivery. The fate of American AI leadership is increasingly tied to the adequacy of its electric grid. Reliable, secure, and dispatchable power is a strategic enabler for AI and the broader economy. DOE's microgrid AI efforts therefore contribute to national goals of energy security, economic competitiveness, and global technological competitiveness – strengthening grid reliability and resilience (to reduce blackouts), enhancing security (against cyber and physical threats), and improving dispatchability of resources (to meet load under all conditions). These efforts are also consistent with the Genesis Executive Order's emphasis on secure, trustworthy AI for critical infrastructure and national security–relevant applications.

DOE offers unique value that accelerates innovation beyond what industry or academia can achieve alone. The Department convenes extensive cross-laboratory and stakeholder collaborations. Moreover, DOE de-risks new technologies by supporting rigorous testing and validation. Early-stage solutions are evaluated in stages (from simulation to lab prototypes to field trials) to ensure they will perform in real conditions. For example, DOE partnered with industry to validate a 70 MW data center microgrid at scale through the Vulcan Test Platform, demonstrating that such systems can provide critical grid services under real-world conditions (Vaidhynathan et al. 2025). This de-risked, scalable deployment through cyber-secure unit and functional testing toward full-scale field validation approach reduces the adoption risk for utilities. DOE also serves as a neutral convenor for stakeholders – utilities, regulators, tech developers, and end-users – building consensus on standards, sharing data and results, and aligning R&D with real-world needs. All these roles ensure the U.S. maintains leadership in AI-driven grid innovation, by smoothing the path from lab innovation to reliable deployment.

Another key rationale for sustained DOE investment is that many AI/ML capabilities vital to microgrids are not yet commercially mature. For example, AI models must be rigorously validated and made explainable for operators to trust them in mission-critical grid control. Developing physics-informed, interpretable AI and thorough verification & validation (V&V) protocols is a pre-commercial challenge that DOE is uniquely positioned to lead. Similarly, deploying AI at the edge of the grid (in controllers at microgrid sites) demands handling large volumes of real-time data from many distributed devices. Techniques for such scalable, edge AI control including emerging techniques like federated learning are still in nascent stages. These are not areas where vendors will invest heavily on their own, given uncertain ROI and the need for fundamental R&D breakthroughs. DOE's leadership and funding are essential to push these technologies from concept to operational readiness. By doing so, DOE fills the "innovation gap," enabling explainable, certified AI microgrid controllers, resilient networked microgrids, and other capabilities to eventually transition into the marketplace.

Looking ahead, OE's role can be viewed along a 10-year trajectory (2026-2036). Over the next 18 months (2026 to mid 2027), DOE can focus on defining both technical and user requirements, curating data sets, and demonstrating early AI/ML prototypes for targeted reliability and resilience use cases. This will evolve into efforts targeted for the next five years (2026-2031), in which DOE can drive intensive R&D, human-in-the-loop field validation, and pilot-scale demonstrations to advance these capabilities toward approximately TRL 6. During this window, OE can leverage National Laboratory individual and federated testbeds for rigorous testing and evaluation. With the established technologies, DOE's role over the longer time period (2031-2036) shifts toward enabling larger-scale pilots, codes and standards, and technology transfer, with industry increasingly leading deployment as solutions reach higher TRLs and proven business cases.

In summary, DOE's role in AI/ML for microgrids is to lead the national effort to scale intelligent, secure, cost-effective microgrids across critical infrastructure and energy-intensive sectors. This forward-looking, strategic R&D agenda will ensure the U.S. retains energy dominance and AI leadership in the power domain. By investing in foundational AI/ML tools for visibility, control, protection, and self-healing response, DOE/OE de-risks innovations that enhance grid reliability and resilience. Its cross-cutting initiatives and partnerships accelerate innovation and set the stage for industry uptake. Crucially, this work is structured to show tangible reliability, resilience, and affordability benefits within shorter timeframes, while charting a clear pathway from early-stage research to industry-led deployment over the 5–10 year horizon. The clear vision is that through DOE's leadership, AI-driven microgrids will evolve from niche demonstrations into widespread, operational assets – autonomous microgrid networks that fortify the nation's grid, fuel economic growth, and protect communities in an era of emerging challenges and opportunities.

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