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Frontiers in Energy Storage: Next-Generation Artificial Intelligence (AI)

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Disclaimer

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Abstract

The Department of Energy's (DOE) Office of Electricity (OE) sponsored the "Frontiers in Energy Storage: Next-Generation Artificial Intelligence (AI) Workshop", which was hosted at Lawrence Berkeley National Laboratory on April 16, 2024. This hybrid event convened industry leaders, researchers, and innovators both in-person and virtually to discuss the transformative potential of AI in enhancing the development and adoption of grid-scale energy storage. Participants presented and discussed how advancements in machine learning (ML) and AI can catalyze innovation in material development, system integration and optimization, performance validation, and strategic policy development.

The wide-ranging workshop spanned topics from accelerated materials development to policy and valuation of long duration energy storage systems as well as the use of AI-powered agentic systems to manage grid operations. Throughout the event, participants highlighted the technical, social, and financial hurdles in building and maintaining robust data infrastructures that serve as the foundation for AI/ML innovation. Key recommendations were made across the entire range of topics, with clear needs for the development of scalable and trustable AI tools, enhancement of data availability and interoperability, the need for interpretability and transparency in policy decisions, and promotion of cross-sector collaboration to realize the full potential of AI in energy storage. Additionally, the workshop underscored the importance of fostering collaboration between academic/government researchers and industry to fully unlock the potential of AI in energy storage and grid operations.

This report summarizes these discussions, with the goal to guide and inform future advancements of AI for energy storage that align with national goals for energy efficiency and sustainability.

Workshop scope and format

The Department of Energy's (DOE) Office of Electricity (OE) held the Frontiers in Energy Storage: Next-Generation Artificial Intelligence (AI) Workshop, a hybrid event that brought together industry leaders, researchers, and innovators to explore the potential of AI tools and advancements for increasing the adoption of grid-scale energy storage. The event was in-person on April 16, 2024 at the Lawrence Berkeley National Laboratory. Virtual attendance was also available.

Scope: Grid-scale energy storage is a key component of the clean energy transition. Machine learning (ML) and artificial intelligence (AI) can drive innovation in areas like advanced material development, performance validation, and decision-making tools. They have the potential to play a significant role in meeting future demands for long-duration, grid-scale energy storage technologies. Workshop participants examined the potential for meaningful impact in this dynamic field through presentations, panels, lightning talks, and interactive breakout sessions. A major goal of the workshop was to brainstorm and identify key opportunities and recommendations for intervention by the DOE, labs, and industry.

Format: The workshop was divided into a morning session centered on talks / panels and an afternoon session dedicated to breakouts and discussion. The overall structure of the agenda included:

- Remarks from the Department of Energy
- Invited presentations on national lab capabilities
- Invited presentations from industry and consultants
- A panel discussion on markets and deployment
- "Lightning talks" on technical topics
- Breakout discussions with three parallel topics:
    - AI for Enhancing Energy Storage Materials and Systems
    - AI for the Design, Control, and Operation of Energy Storage Technology
    - AI for Valuation, Markets, and Policy for Accelerating Energy Storage Deployment
- Joint report-outs and discussion of breakout room recommendations

Participant statistics: A total of 248 attendees attended the workshop. Of the attendees, 59 were in-person and 189 were virtual.

Introduction and workshop themes

The workshop was organized around three core themes, each exploring a crucial aspect of the intersection between energy storage and AI.

Energy Storage – Materials, Manufacturing and Systems Development
This theme focused on how AI and ML techniques can discover novel materials and improve forecast of the performance of existing storage systems. Participants discussed how AI models can accelerate the discovery and optimization of new battery materials by analyzing vast datasets and predicting properties that would traditionally require labor-intensive experimental work. They also discussed rapid validation of new energy storage systems to project performance under various operating conditions and after long deployment periods.

Incorporating AI into Grid Operations
The second theme addressed the potential of AI-driven models to revolutionize the design, operation, and maintenance of energy storage systems. Conversations explored predictive maintenance techniques, operational optimization strategies, and control algorithms that can improve the efficiency and lifespan of storage units while managing concerns regarding security and interpretability, and protecting against unintended side effects. These aspects all together can be portrayed as an autonomous energy storage concept that makes real-time decisions and controls its operations based on environmental signals (Market) and internal states (efficiency, health, etc), predicts its potential failure scenarios/maintenance requirement, and takes care of its safety and [cyber]security.

Valuation and Policy Decisions Regarding AI and Energy Storage
This theme investigated how AI can inform storage valuation, market dynamics, and policy-making, including use of "generative AI" and LLMs for high-level market / policy studies and use of machine learning / deep learning / reinforcement learning techniques for technology valuation and energy systems analyses. It underscored the need for transparent data management and sophisticated modeling to evaluate market trends and inform regulatory strategies in a manner that ensures fairness. By incorporating AI into decision-making processes, the energy sector can better understand the complex interactions between technology, policy, and economics.

These themes laid the foundation for collaborative discussions and were discussed in detail later in this report. However, in discussing these themes, a foundational theme emerged: data and computing. This topic, which had common elements across each of the three themes, is discussed next.

Foundations of AI/ML: Data and Computing

Data and computing emerged as foundational themes throughout the workshop discussions. Availability, management, and security of data were all critical considerations for developing and deploying Machine Learning (ML) and Artificial Intelligence (AI) models in the energy storage domain.

The Data Challenge: Acquisition to Preservation

The national labs highlighted successful data infrastructure projects while acknowledging the challenges – both technical and social – involved in building and maintaining these resources. The sheer volume of scientific data generated by the Department of Energy (DOE), the world's largest scientific data producer according to Brian Spears of LLNL, necessitates a comprehensive data lifecycle approach that involves the following steps:

Acquire ⇒ **Transfer** ⇒ **Clean** ⇒ **Use** ⇒ **Publish** ⇒ **Preserve**

Examples of successful data infrastructure projects presented at the workshop include:

- **ESS-DIVE** (Earth System Science Data Infrastructure for Virtual Experiments)
- **Ameriflux** (a network of research towers measuring carbon dioxide, water vapor, and energy exchange)
- **The Materials Project** (a large open-access database of materials science data)

The DOE has also funded various "data hubs" tailored to specific scientific domains as part of its Energy Materials Network program, leveraging common infrastructure while addressing unique needs of the various research hubs within the program.

Beyond Scientific Data Management: Unstructured Information and Actionable Insights

Data sets for AI/ML analysis extend beyond those deposited into databases as a product of traditional scientific research. As presented by TDP Data Systems, companies offer access to hundreds of data sources, including paper abstracts, patents, business profiles, funding calls, and census information. These resources, combined with new techniques for analyzing unstructured text data (natural language processing), can provide valuable insights. For instance, AI/ML can be used to analyze the Justice40 map and suggest microgrid locations to address energy inequities, or identify companies working at the intersection of AI and energy storage. National labs such as LBNL and Argonne are also actively developing methods to convert unstructured academic literature text and data plots into structured data sets suitable for AI/ML applications. Such developments offer the potentially to greatly expand the quantity of data that can potentially be used for training AI/ML models.

Uncertainty, Security, and Computing Power

The workshop also highlighted other critical considerations for AI/ML in energy storage:

- **Uncertainty and Security:** Labs shared successes in managing uncertainty and security for projects like fusion experiments, climate prediction, and the FASST program centered at LLNL.
- **Computing Capability:** Several labs, including ORNL, Argonne, LLNL, and LBNL, house powerful supercomputers that can be leveraged for AI workloads. However, the energy consumption of these machines raises concerns about cost, environmental impact, and infrastructure strain.
- **Foundational Science Models:** ORNL introduced the concept of using DOE HPC systems to train multiscale, multimodal foundation models that can be adapted for various scientific applications. The development of such foundational models could accelerate research and development progress across multiple downstream applications.
- **AI/ML Paradoxes:** ORNL also presented several "paradoxes" associated with AI/ML, including:
  - Easy to demonstrate but challenging to implement in production.
  - Struggle with simple problems despite solving difficult ones.
  - Face an ever-growing set of unresolved research challenges.
  - Often road blocked by human behavior.
  - Exhibit unique cyber-physical challenges.

These considerations are common to many of the opportunities presented by AI/ML and should be addressed in designing research programs and policy.

The Path Forward: FAIR Data Principles and Addressing Challenges

The presentation from PNNL emphasized the importance of FAIR data principles (Findable, Accessible, Interoperable, Reusable) to enable effective AI/ML development. Strategies for addressing data challenges included better data curation, more facile data sharing, few-shot learning (machine learning with minimal data), and the use of domain-specific foundation models. More specific recommendations were also made within discussions for each of the three themes, which are detailed next.

Theme 1: Energy Storage – Materials, Manufacturing and Systems Development

Developing innovative materials that serve as the basis for new storage technologies involves exploring a vast parameter space (composition, structure, synthesis, processing). Traditional parametric studies are slow, involving lengthy synthesis and testing phases guided by researcher intuition. AI offers efficient exploration methods, overcoming these limitations and helping identify optimal materials. Furthermore, once a new energy storage system is identified, AI can help validate and optimize the long-term performance of that system.

Current capabilities

Current capabilities of AI in energy storage development include surrogate models for expensive and high-fidelity simulations, autonomous experimentation, and long-term performance projection. Surrogate models for Density Functional Theory (DFT) calculations achieved through machine learning can provide high accuracy in predicting materials properties at several orders of magnitude lower computational expense than direct simulation. They enable researchers to explore large parameter spaces quickly, facilitating the discovery of new materials and optimization of existing ones.

Emerging AI-powered autonomous experimentation systems enhance these rapid materials discovery pipelines, providing rapid hypothesis testing and creating efficient optimization loops that can "self-drive" towards desired results. Such systems, which have the potential to operate 24/7, can explore the parameter space of new materials and manufacturing techniques at a much more rapid pace including the use of AI/ML to steer the decision-making of the lab. However, their adoption is not yet widespread due to their upfront cost and technical barrier of developing the software, hardware, and overall protocols for the lab. Such barriers often must be overcome individually for each new project. For instance, some industry institutions have achieved inline metrology capabilities but are not shared with other research institutions.

Capabilities mentioned during the workshop for accelerated materials development include:

- **The Materials Project**, a resource with nearly 500,000 registered users that contains property data on known and hypothetical materials as compiled from high fidelity simulations (LBNL).
- **The A-lab**, a robotic and autonomous lab for the synthesis and characterization of new materials via scalable solid-state synthesis methods (LBNL).
- **ARES lab** - an automated research for energy storage lab that uses robotics for liquid handling and synthesis of materials samples (PNNL).
- **AI models for new energetic molecules** (i.e., molecules with high density and high heat of formation), with AI-generated molecules providing new candidates at the limits of known molecules (LLNL).
- **AI-accelerated design of chromophores** (applications in biomedicine, MRIs, and quantum circuits) in which AI can potentially filter billions of potential candidates in hours (ORNL).
- **SOMAS database** - a database for solubility of organic molecules in aqueous solution (PNNL).

Furthermore, new long-duration energy storage technologies require performance projections over decades despite limited testing periods. Several labs highlighted capabilities to address this:

- **ROVI Initiative**: DOE-supported, rapid validation of new technologies using an in-situ parameter extraction protocol. The protocol merges measurements from bench scale experiments, small cells, and large stacks to predict performance across length scales. The initiative is currently developing digital twins for redox flow batteries (six lab consortium).

- **Gaussian Process-Based Failure Prediction**: Predicts failure probabilities across multiple factors such as cycle count, C-rate and state of charge. Fast validation of grid energy storage solutions can be achieved using physics-informed Gaussian processes and AI sequential sampling which also enable accurate extrapolation and uncertainty quantification (LBNL).

Gaps and challenges

The adoption of AI in energy storage is still low due to several challenges, with many of the identified challenges centered around data:

- **Limited Data Volume:** Essential data, such as internal battery states during cycling and experimental data on materials properties, is scarce.
- **Data Sharing Barriers:** Lack of standardized formats and metadata makes combining / merging data sets challenging even when they exist.
- **Industry Data Sensitivity:** Proprietary data is rarely shared; inadequate anonymization protocols make it challenging to practice data sharing even when it is desired.
- **Difficulty of multiscale modeling:** Limited applicability of simulation models to long-term performance and degradation due to gaps in time and length scales of achievable modeling frameworks, particularly for new materials.

Recommendations

The following list of recommendations were a result of the discussions around this theme:

1. **Data sharing and standardization**
    a. Leverage experience of national labs to establish a consortium to share data, including "bad data," with conditional funding and anonymization protocols.
    b. Create a protocol to anonymize data or generate synthetic data for safe sharing.
    c. Investigate motivational factors for industry participation in a data and methods-sharing consortium, perhaps focusing on "pre-competitive" activities.
    d. Provide a comprehensive data repository and data dissemination guidance for self-upload of data. Couple the repository with a discoverability tool so researchers can easily share data.
    e. Consider federated learning or similar approaches to facilitate data exchange.

2. **Integrate accelerated materials design approaches with industry**
    a. Foster connections between various accelerated materials design efforts and industry; create a pipeline connecting academic device prototype and industrial production scales.

b. Encourage the development of autonomous laboratories with common components to reduce the barrier and cost for new laboratories.
c. Create surrogate machine learning models that are cheaper and faster than density functional theory calculations and that can rapidly assess the characteristics of new energy storage materials.

3. **Battery monitoring and supply chain**
   a. Use AI to monitor batteries at the cell level, minimizing fire risk and empowering underwriter decision-making. Re-work the design of batteries from materials to cell level to minimize fire risk.
   b. Expand AI's role in developing battery materials to address supply chain challenges, as less than 10% of batteries are manufactured in the U.S.
   c. Establish infrastructure for battery recycling and lifecycle management.

Theme 2: Incorporating AI into Grid Operations

The application of AI in energy storage systems holds significant promise across various applications to support data-driven physics-informed decision making. AI offers the possibility to extend the lifespan of storage assets by suggesting optimal usage patterns and charge/discharge cycles to minimize degradation or maximize economic value. AI-powered algorithms can also support maintenance decisions, analyzing the cost-effectiveness of adding new batteries versus rebalancing loads across existing ones.

For grid operations, AI can address the challenges arising from an increasing number of distributed energy resources such as solar and electric vehicles. AI, coupled with big data systems, can perform faster load flow analyses to manage grid contributions from these sources. Notably, AI's ability to rapidly process large datasets surpasses traditional optimization models, enabling faster and more comprehensive decision-making.

Current capabilities

The deployment of next-generation storage technologies necessitates more complex grid operations. AI and digital twins can significantly aid in storage deployment planning, real-time operations, and impact assessments. Several labs presented their work in this area:

- **Superlabs:** Digital twins communicating via ESNET, integrating models from various labs (e.g., Flexlab, ARIES).
- **Urban digital twins:** Leverages street view analysis to generate digital cities for planning and deploying storage at scale (LBNL).
- **AI-based failure prediction:** Optimizes power system decision-making during disasters like wildfires based on risk modeling (LBNL).
- **AI-based battery dispatch:** Optimizes battery usage for grid resilience and voltage control (LBNL).

- **Darkstar:** AI-based inverse design of complex hydrodynamics, shockwave physics and energetic materials (LLNL).
- **Manufacturing digital twins:** Digitized parts and processes for production acceleration (LLNL).
- **Rapid AI controls:** AI control of high-repetition-rate lasers that could potentially be adapted for grid components (LLNL).
- **AI-based accelerator tuning**: Significantly reduces tuning time; e.g., the Scorpius accelerator is tuned via an AI-based model and optimizer that delivers 40-hour human tuning in minutes (LLNL).
- **Grid resilience and intelligence platform:** Data-driven scenario analysis for mitigation planning (Arras Energy, SLAC).
- **Future nuclear power plants with Thermal Energy Storage (TES):** Provides flexibility for grid balancing and economic optimization (Idaho National Laboratory).

The concept of an **agent-based marketplace** was introduced, where individual AI entities autonomously manage tasks. Examples include transformer chips making localized decisions while coordinating with a larger model for overall strategy (Resonet systems). The discussion also highlighted the importance of combining AI with **IoT (Internet of Things)** to facilitate communication and coordination between devices, leading to complex and adaptive behaviors. **Digital twins** were also introduced; a key distinction between simulations and digital twins is that digital twins incorporate real-time data from real-world objects. This enables applications like predictive maintenance, operational optimization, and product development tailored to a specific physical entity. Digital twins can also be instrumental in planning smart grids, which will be significantly more complex than traditional grids.

Speaker Robert Akscyn emphasized the potential of AI/ML (Machine Learning) for rapidly exploring vast design spaces, such as configuring holistic energy storage systems that leverage synergies between different systems (*e.g.*, offshore wind power combined with other storage solutions). AI/ML can analyze cost-benefit ratios of various designs at scale, ranking solutions, generating new options, and performing in-depth analyses. Symbolic reasoning integration might be necessary, particularly for interpretability / transparency purposes.

Gaps and challenges

The workshop identified key challenges hindering widespread adoption of AI in coupling energy storage with grid operations:

- **Access to Data:** Security concerns limit the availability of real-world storage data, creating barriers for validation and improvement of AI algorithms.
- **Trust and Interpretability:** Users require transparency on how results are obtained. AI needs to ensure safety, provide "fail-safe" options, and flag issues that humans might overlook. Symbolic reasoning and explainable AI were noted as necessary features to enhance adoption and trust.

- **Data privacy, security, and cybersecurity considerations**: Privacy and security must be addressed for the "agentic" grid to be deployed in practice without introducing unintended side effects.
- **Energy Consumption:** The high computational demands of AI could hinder its adoption if not balanced with efficient energy consumption.

Recommendations

The workshop identified the following recommendations for overcoming the gaps:

1. **Optimizing AI Infrastructure and Tools**
   a. Develop scalable, deployable, and explainable AI tools to build trust in their solutions.
   b. Provide community data sets for training AI-controlled infrastructure, or provide realistic synthetic datasets if real-world data is unavailable.
   c. Use digital twins and model predictive control to optimize energy systems using external data inputs like weather forecasts.
   d. Study the balance between the energy consumption efficiency of AI approaches and their performance.
   e. Establish infrastructure for processing data from distribution systems to facilitate AI operations.

2. **Enhancing AI Applications in Grid Operations**
   a. Test deployments that utilize AI for system control, degradation analysis, and storage cycle life predictions.
   b. Explore, test, and validate methods for secure communications from telemetry systems to AI models so that critical measurement data is not leaked.
   c. Explore future AI use cases in vehicle-to-grid (V2G) demonstrations.
   d. Examine AI's potential in optimizing second-life battery usage.
   e. Simulate the use of agent-based models to optimize energy markets, potentially under traditionally difficult constraints such as with batteries at different stages of degradation.

3. **Coordination and Knowledge Dissemination**
   a. Develop standards for replacing classical mathematical approaches by AI, and the resulting trade-offs and benefits.
   b. Educate the public and disseminate AI-related knowledge for grid operations.
   c. Foster connections between different DOE offices to align their AI research objectives.

Theme 3: Valuation and Policy Decisions Regarding AI and Energy Storage

Artificial Intelligence has significantly influenced how the energy sector approaches the future of storage valuation, market dynamics, and policy-making. The emergence of generative AI represents another significant advancement with the potential to reshape the energy storage ecosystem, influencing its valuation, management, and integration into broader energy policies. This section draws on discussions with industry and national lab experts to explore how AI can be leveraged to accelerate energy storage deployment. It highlights current AI capabilities, prevailing challenges, and proposes strategic actions.

Current capabilities

Existing AI technologies, including regression models, deep learning/machine learning models, symbolic models, and expert and multi-agent systems, offer various functionalities relevant to energy storage system valuation. These include:

- **Short-term market trend forecasting**: Based on historical data under normal conditions, such systems identify storage dispatch strategies to maximize energy market value. Companies like Vistra have deployed such technology to operate their storage units in California.
- **Long-term demand and supply analysis**: Such analyses can project future energy needs and infrastructure development. For instance, agent-based models like BEAM CORE (developed at Berkeley Lab) simulate populations and firms (as agents with objectives) competing for resources. This model has been used in co-simulation with a grid model to perform sensitivity analyses of behind-the-meter storage in scenarios with high EV penetration.
- **TEA models for long duration energy storage technologies:** Techno-economic analysis capabilities determine the projected cost of the energy storage materials for yielding certain performance or levelized cost of electricity (USD/kWh), can be used to determine if future storage system proposals could be viable. (NETL, LBNL)
- **PolicyAI**: Developed at PNNL, PolicyAI provides insights to expedite environmental and permitting reviews. Such AI models can inform stakeholders about optimal investment strategies (grid upgrades for storage integration or distributed energy resource deployment) and public policy improvements impacting storage siting.
- **Formware:** Form Energy, a commercial developer of multi-day iron-air batteries, introduced Formware, a grid modeling software tool for capacity expansion planning, economic dispatch, and reliability/adequacy assessments. Customers leverage this software to understand the benefits of long-duration and multi-day energy storage solutions, considering various technologies and scenarios. To achieve a more accurate valuation of long-duration storage in a given energy portfolio, Formware uses 8760-hourly resolution and co-optimizes multiple weather-year and investment-year scenarios. Assessing overlapping scenarios with this level of detail can sometimes hit computational limits. AI/ML could

potentially help overcome these limits by taking large-scale optimization problems (mixed integer programming, linear programming, etc.) and downsizing the problem (e.g. through representative period selection, decomposition) and/or reducing the solution space (e.g. warm start, branch and cut) in a way that a solution can be achieved much faster than with traditional methods.

Gaps and challenges

Despite these capabilities, AI technologies face several challenges as identified during the workshop:

- **Access to data** - It is difficult to acquire empirical data due to limited access and availability, impacting accurate forecasting. AI models relying on historical data might perpetuate outdated frameworks, particularly those favoring environmentally harmful production or creating inequity.
- **Long-term forecasting** - Market and technological developments are unpredictable, making it challenging to generate accurate long-term forecasts using past data.
- **Managing complexity in policymaking** - AI tools must balance sophistication and simplicity to be comprehensible to decision-makers. Some decisions require negotiation and human judgment that cannot be fully replaced by AI (*i.e.*, are difficult to translate to clear AI objective functions). Finding a proper balance between computer assistance and human engagement in policymaking is challenging.
- **Transparency, accountability, and justice** - Generative AI systems typically have a black-box nature, complicating interpretability, decision transparency, and regulatory accountability. There may be a potential for AI models to reinforce biases that favor certain communities or perpetuate environmental harm and in a way that is difficult to detect.
- **Cybersecurity** - Ensuring AI models are safe and trustworthy is crucial, particularly in managing sensitive energy data.

Recommendations

The workshop identified the following recommendations for overcoming the challenges in this area:

1. **Data Management and Analytics**
    a. Invest in programs that train AI models with up-to-date and diversified data sets and with algorithmic fairness to reflect current environmental priorities and market conditions; encourage and support the development of new empirical datasets on energy storage behavior.
    b. Develop platforms that link (and/or integrate) datasets across various sectors to enable generative AI models to provide comprehensive insights that inform energy storage valuation and policy-making.

c. Implement standards and frameworks that increase the interpretability and interoperability of AI decisions in energy storage management and regulatory oversight to enhance transparency and accountability.

2. **Support for Innovation and Infrastructure Development**
    a. Increase support for under-resourced government agencies by providing well-trained and calibrated AI tools that assist in technical evaluations and decision-making processes and can be fine-tuned for specific purposes.
    b. Address cybersecurity concerns and ensure AI models are safe and trustworthy, especially considering the increasing complexity and interconnectedness of energy systems.
    c. DOE and FEMA should continue to sponsor initiatives like the installation of microgrids to optimize solar and battery placement, reducing damages from loss of transmission lines during disasters, and begin integrating AI into such projects.
3. **Public Engagement and Policy Enhancement:**
    a. Educate the public on the use of AI/ML to ensure its utilization and adoption, focusing on understanding new energy technologies, the opportunities and challenges of new AI/ML-based models, and choices regulators face and the criteria they use for decision-making.
    b. Enhance grid resilience against more frequent extreme weather events through AI that predicts and prepares for such events, ensuring storage systems are part of a resilient infrastructure.
    c. Start a consortium of AI researchers focused on identifying useful applications of AI technologies and filtering out issues that are not improved by AI; include applications in refining insurance underwriting processes and facilitating more accurate oversight of energy storage assets to mitigate market power risks.

Conclusion and summary

The Frontiers in Energy Storage: Next-Generation Artificial Intelligence (AI) Workshop showcased the tremendous potential for AI and machine learning (ML) to transform energy storage at the grid scale. By bringing together experts from industry and government, the workshop fostered insightful discussions on key themes spanning the entire range of this broad topic. Discussion themes included accelerated materials development, strategic decision-making, and the effective integration of AI tools into grid management.

A recurring message from the workshop was the challenges of building robust data infrastructures; participants emphasized the need for technical, social, and financial investments to drive this transformation. Other recommendations included highlighting the importance of scalable and transparent AI tools, comprehensive data availability, and fostering cross-sector collaboration. Ultimately, such foundational efforts will align with broader national goals of sustainability and energy security, providing the opportunity for an increased role of AI and energy storage in shaping the future of the grid.