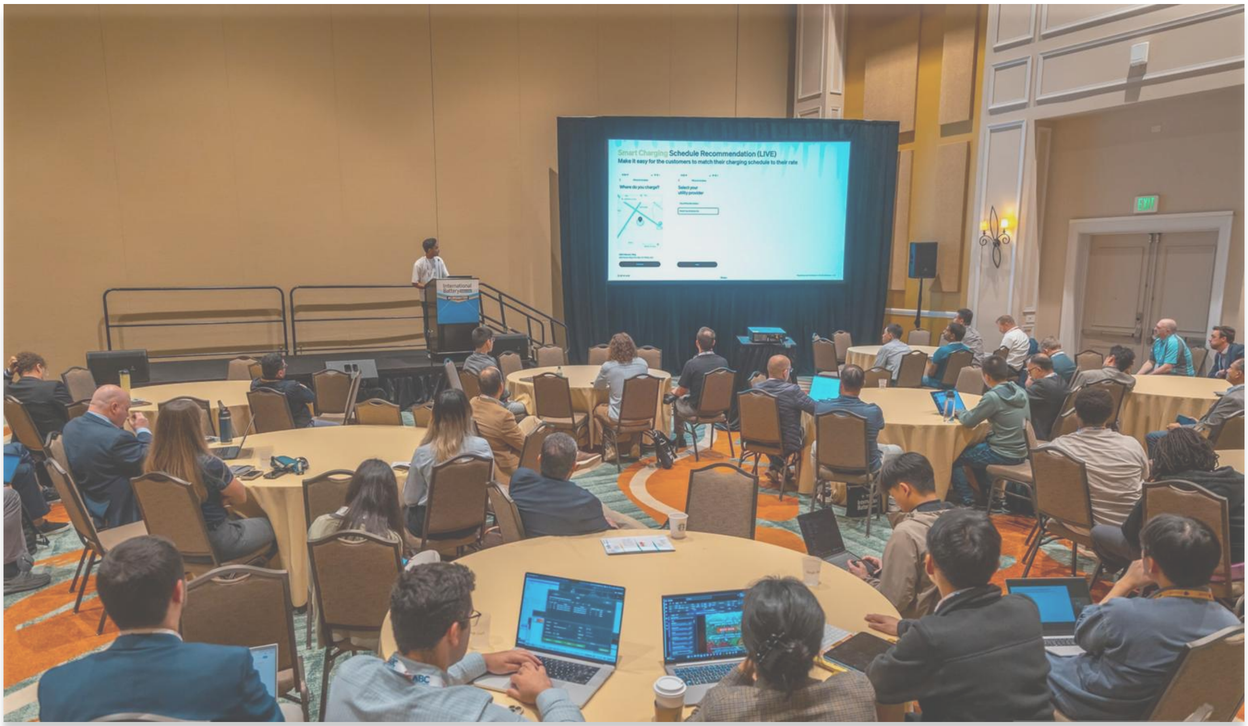
International Battery SEMINAR & EXHIBIT



2026 Conference Track Summary –

AI for Energy Storage

Brought to you by Cambridge Healthtech Institute, a division of Cambridge Innovation Institute

250 1st Ave, Suite 300, Needham, MA 02494
T: 781.247.6262

Executive Overview

The 2026 International Battery Seminar & Exhibit AI in Battery Technology track demonstrated that artificial intelligence is evolving from a research tool into a practical technology for designing, manufacturing, operating, and managing next-generation battery systems. Across presentations, speakers emphasized that the greatest advances come from combining machine learning with physics-based understanding, enabling faster development without sacrificing engineering insight. Discussions spanned the full battery lifecycle—from material and electrode design through manufacturing, battery management, grid integration, and field operation—highlighting how connected data, predictive models, and digital twins are accelerating innovation while improving reliability, efficiency, and real-world performance.

Most Frequently Covered Issues

1. Physics-informed AI and machine learning
Hybrid models are improving prediction accuracy while maintaining the interpretability needed for engineering and manufacturing decisions.

2. Accelerated battery development
AI is shortening design cycles through adaptive testing, generative design, intelligent experimentation, and earlier prediction of long-term performance.

3. Battery manufacturing and quality optimization
Production data, advanced imaging, and digital characterization are improving quality control, reducing testing, and enabling more consistent manufacturing.

4. Intelligent battery operation and energy management
AI is enhancing battery management systems, grid integration, charging optimization, and large-scale energy-storage operations through predictive monitoring and decision support.

5. Digital twins and connected data ecosystems
Integrated digital platforms are linking laboratory data, manufacturing, and field performance to support continuous improvement across the battery lifecycle.

Recurring Takeaways

- AI delivers the greatest value when combined with physics-based models and engineering expertise.
- Earlier access to predictive insights reduces development time and experimental effort.
- Connected manufacturing and field data strengthen battery quality, reliability, and lifecycle management.
- Digital twins are becoming foundational tools for design, operation, and optimization across battery systems.
- Future battery innovation will increasingly depend on integrating materials science, manufacturing, software, and AI into a unified development framework.

AI in Battery Technology: From Laboratory Testing to Field Applications

Full Video Here

Weihan Li, Junior Professor, RWTH Aachen University

Battery development increasingly sits between two extremes: limited, clean data where physics is well understood, and massive field datasets that are noisy, incomplete, and difficult to model physically. Combining machine learning with physics-based models can bridge that gap, improving diagnosis and prediction while keeping results interpretable enough for engineering decisions. (00:03:00–00:06:58)

Production and characterization offer immediate opportunities to shorten feedback loops. Formation data can support early quality classification and lifetime prediction, while AI-assisted parameterization and imaging can extract richer information without lengthy destructive testing, helping manufacturers identify variability and performance problems sooner and reduce testing effort. (00:06:58–00:13:16)

Adaptive testing can further compress development timelines by combining physical models, machine learning, and real-time experimentation. Closed-loop approaches continuously update aging predictions and adjust test conditions, while surrogate models and transfer learning can reuse knowledge across cell generations, reducing repeated testing as products evolve. (00:13:16–00:18:41)

Field data creates a different opportunity because scale compensates for imperfect labels and noisy measurements. Statistical and self-supervised methods can connect controlled laboratory knowledge with real-world behavior, improving health estimation, anomaly detection, and maintenance, while AI agents can make battery-system expertise more accessible to engineers operating large energy-storage assets. (00:18:41–00:25:43)

Key Takeaways

- Hybrid physics and AI models balance predictive power with engineering interpretability.
- Earlier use of production data can reduce costly downstream testing.
- Adaptive testing and transfer learning can shorten battery development cycles.
- Connecting laboratory and field data strengthens diagnosis, prognosis, and maintenance.

Characterization and Design of Battery Electrodes with Generative AI

Full Video Here

Isaac Squires, CEO, Polaron

Battery microstructure forms a critical bridge between manufacturing processes and cell performance, influencing transport, rate capability, and degradation. Yet microscopy remains heavily dependent on manual interpretation, limiting the speed, consistency, and resolution of material insights needed to connect processing choices with performance outcomes. (00:01:29–00:07:24)

AI-based image segmentation can turn complex microscopy data into quantitative measurements of active material, porosity, binder distribution, particle morphology, and degradation. Robust models can also accommodate multiple imaging signals and common artifacts, creating faster, repeatable workflows for comparing materials, diagnosing production differences, and tracking phenomena such as electrode cracking. (00:07:24–00:14:21)

Generative reconstruction extends those insights from two-dimensional images into three-dimensional structures, providing access to transport properties that are otherwise difficult and time-consuming to measure. Validated against real 3D imaging, these reconstructions can rapidly estimate parameters such as tortuosity, conductivity, diffusivity, and particle distributions for higher-fidelity electrochemical modeling. (00:14:21–00:19:11)

Once microstructure can be measured reliably, generative AI can help explore how to improve it. Virtual experiments can evaluate material ratios, layered architectures, porosity, particle distributions, and processing conditions, linking promising structures back to realistic manufacturing windows and allowing thousands of potential electrode designs to be screened before committing to physical experiments. (00:19:11–00:24:38)

Key Takeaways

- Microstructure connects battery manufacturing choices directly to performance.
- AI converts microscopy images into faster, repeatable quantitative characterization.
- Generative reconstruction makes difficult 3D transport insights more accessible.
- Virtual design can identify promising, manufacturable electrodes before extensive experimentation.
- Structural design can control glycosylation patterns and other complex biochemical properties.

Battery Intelligence Approach for Large-Scale BESS

Full Video Here

Wenjiao Huang, Principal Battery Research Data Scientist, Fluence

Large-scale battery storage creates a monitoring challenge as fleets grow from thousands of cells to gigawatt-hour systems. Uneven aging, partial cycling, thermal gradients, operational surprises, and safety requirements make conventional monitoring increasingly difficult, while maximizing short-term market revenue can also accelerate degradation if battery health is ignored. (00:00:00–00:05:24)

Accurate health estimation must account for interacting stress factors rather than treating temperature, state-of-charge windows, discharge depth, and C-rate independently. LFP chemistry adds difficulty because its relatively flat voltage profile limits conventional voltage-based BMS estimates, making cloud-based intelligence useful for tracking changing health conditions across diverse operating environments. (00:05:24–00:09:14)

Real-time health and balance monitoring can identify pack-level inconsistencies before they reduce available energy or cause lasting degradation. Remaining useful life forecasting adds another decision layer by evaluating how dynamic operating profiles affect degradation, helping operators select dispatch windows, plan maintenance, assess warranties, and schedule augmentation when economic value is highest. (00:09:14–00:16:04)

Battery fleets also create an expanding source of operational data that can improve forecasting as experience accumulates. Combining laboratory results, engineered field features, and degradation models supports increasingly precise control, while physics-informed approaches and digital twins offer a path toward more reliable prediction as systems become larger and more complex. (00:16:04–00:23:36)

Key Takeaways

- Large-scale BESS requires intelligence beyond conventional cell and pack monitoring.
- Battery health and market dispatch should be optimized together.
- Real-time health and balance insights support better maintenance and operating decisions.
- Combining field data with physics-informed models can strengthen long-term forecasting.

Optimizing Hybrid Battery Packs with Multiple Cell Chemistries

Full Video Here

Ricardo Pinto de Castro, PhD., Professor, University of California, Merced

No single battery chemistry performs strongly across every requirement, so selecting one typically means accepting compromises in energy, power, temperature performance, safety, or cost. Hybrid battery packs create another design option by combining chemistries with complementary strengths, allowing the system to draw on different characteristics as operating needs change. (00:00:00–00:04:49)

Designing these packs requires more than pairing two cell types. Mission profile, power and energy requirements, temperature, volume, cost, emissions, power electronics, and power-sharing strategy can be incorporated into an optimization framework that determines how much of each chemistry is appropriate for a specific application. (00:07:45–00:10:22)

For light EVs, combining high-energy NMC with high-power LTO can avoid the oversizing that occurs when either chemistry must satisfy both power and energy demands alone. Modeling showed potential pack-mass reductions ranging from 5% to 60% depending on the driving cycle, with the strongest benefits emerging as applications require both range and power. (00:10:22–00:16:09)

Drone applications reveal a similar opportunity because takeoff and landing demand power while cruising requires energy. Pairing complementary silicon-anode cells improved modeled pack-level energy density by roughly 10% to 11% and landing voltage by 18%, although added electronics increased volume, highlighting the importance of evaluating hybridization against application-specific trade-offs. (00:16:09–00:22:21)

Key Takeaways

- Hybrid packs can combine complementary strengths that no single chemistry provides.
- Application requirements should determine the optimal chemistry mix.
- Dual-chemistry designs can reduce oversizing when both energy and power matter.
- Added electronics, controls, and volume must be weighed against performance gains.

Using AI to Maximize BESS Performance and Longevity

Full Video Here

Craig Mauel, Manager ESS Services, Saft

Large battery storage systems generate millions of operational signals that can support much more than basic monitoring. Bringing battery, power conversion, control, and power-quality data into a secure cloud environment creates a common view of system health, while contractual KPIs help operators manage availability, throughput, efficiency, and operating conditions over a 15-to-20-year lifecycle. (00:01:47–00:07:20)

Real-time status and historical records give service teams a clearer path from an alert to its underlying cause. Trending voltage, current, power, state of charge, temperature, controls, and equipment status together can reveal relationships that isolated alarms miss, enabling earlier intervention and reducing the time required for remote troubleshooting. (00:07:20–00:16:50)

Generative AI can make these large datasets easier to navigate by allowing technicians to ask operational questions in natural language and quickly generate graphs, heat maps, and diagnostic guidance. This approach helps narrow millions of data points to relevant signals, while detailed trending remains available for deeper investigation and confirmation. (00:16:50–00:20:47)

Outlier detection extends monitoring beyond fixed BMS thresholds by identifying subtle deviations before conventional warnings appear. Examples included an abnormal cell-voltage pattern and a container running consistently warmer than its peers, allowing technicians to isolate faulty components before the conditions became larger performance or aging problems. (00:20:47–00:28:16)

Key Takeaways

- Centralized operational data creates a stronger foundation for long-term BESS management.
- Correlating multiple signals accelerates root cause analysis and predictive maintenance.
- Generative AI helps service teams navigate complex datasets more efficiently.
- Outlier detection can surface developing problems before static alarm thresholds are reached.

Accelerating Electrical Interconnections with AI

Full Video Here

John Glassmire, Vice President of Digital Enablement and Transformation, Hitachi Energy

Electricity demand is rising sharply as data centers and AI computing expand, placing new pressure on a grid built around decades of relatively flat demand. AI also offers tools to manage that growth, with applications in predictive maintenance, planning, and operations that can reduce costs and accelerate decisions. (00:04:26–00:07:09)

Transmission interconnection is a major constraint on bringing new generation and battery storage online. Modernizing planning requires more than adding AI alone. Integrated software, centralized and validated data, redesigned processes, and greater computing capacity can work together to shorten studies, improve throughput, and reduce growing project queues. (00:07:09–00:14:59)

Large AI data centers create another challenge because their enormous loads can fluctuate rapidly as computing activity changes. Battery storage can provide a flexible bridge by supporting faster access to power, reducing energy costs, and stabilizing operation, but effective deployment requires coordinated planning and control across the broader electrical system. (00:14:59–00:18:01)

Digital twins extend that coordination by modeling electrical and thermal behavior from the grid through data-center infrastructure before physical changes are made. Combining physics-informed models, unified data, AI optimization, and BESS enables operators to simulate decisions, identify constraints, monitor degradation, and balance grid reliability with compute availability. (00:18:01–00:24:27)

Key Takeaways

- AI-driven demand growth is increasing pressure on grid planning and operations.
- Better data and integrated workflows are prerequisites for effective AI-enabled planning.
- BESS can help manage large, rapidly changing data-center loads.
- Digital twins enable simulation-first planning, operation, and maintenance.

From Molecules to Market: Multiscale Machine Learning and Informatics for Solid-State Electrolyte Design, Integration, and Scale-Up

Full Video Here

Amir Taqieddin, PhD, Principal Scientist, Solid Power

Solid-state batteries involve tightly coupled interactions among materials, interfaces, mechanics, and electrochemistry, making isolated optimization difficult. Physics-grounded machine learning can connect these scales while combining historical experimental data with engineering knowledge, helping teams learn faster without sacrificing the physical interpretability needed to make practical development decisions. (00:00:00–00:04:30)

Early prediction can dramatically shorten the feedback loop between changing a material or process and understanding its impact on cell life. Models using formation-cycle data can forecast long-term behavior within minutes, while physics-based degradation libraries help explain predictions and identify mechanisms rather than returning an opaque performance estimate. (00:05:56–00:16:06)

Failure-mode detection adds another layer by translating early cell signals into probabilities for mechanisms such as plating, void formation, and short circuits. Combining extracted physical parameters with multiscale surrogate models provides engineers with risk indicators, confidence levels, and likely drivers, while active learning allows predictions to improve as new experimental data becomes available. (00:17:16–00:19:49)

Intelligent design of experiments can then move development from prediction toward optimization. Bayesian methods can prioritize influential variables, balance competing objectives, and recommend the next experiment, while interpretable feature relationships and iterative learning help researchers navigate large design spaces with fewer physical tests and clearer connections to real manufacturing parameters. (00:19:49–00:25:43)

Key Takeaways

- Physics-grounded machine learning can connect material, process, and cell-level behavior.
- Early-cycle data can replace months of testing with rapid, interpretable predictions.
- Failure-mode models can identify likely degradation mechanisms and their driving parameters.
- Intelligent experimental design can reduce testing while accelerating manufacturing optimization.

How Rivian Is Using AI to Make EV Charging Smarter

Full Video Here

Yash Gupta, Data Scientist, Rivian

Most EV charging happens at home, yet many drivers begin charging immediately after arrival, including during peak grid hours. As EV adoption grows, unmanaged charging could add significant peak demand, while limited awareness of time-of-use rates and incentive programs leaves substantial opportunities for lower-cost, cleaner charging unused. (00:00:00–00:04:12)

Smart charging can capture much of that value without asking drivers to fundamentally change their routines. Analysis of hundreds of thousands of historical charging sessions found that optimizing within existing plug-in windows could deliver more than 70% of the maximum potential savings, while also increasing renewable energy uptake. (00:04:12–00:09:42)

Making optimization practical requires reducing the effort placed on drivers. Software can identify applicable utility tariffs, recommend lower-cost charging windows, and preserve user control, while AI can extract complex rate structures from utility documents at scale and translate them into charging recommendations that are easier for customers to act on. (00:09:42–00:12:25)

The longer-term opportunity is to coordinate charging around cost, emissions, grid conditions, and individual mobility needs through a simple interface. Cleaner-energy scheduling, managed utility programs, variable charging power, and bidirectional capabilities could progressively expand automation, with human oversight remaining important as optimization becomes more sophisticated. (00:12:25–00:24:32)

Key Takeaways

- Unmanaged home charging can amplify peak demand as EV adoption grows.
- Existing plug-in behavior already provides substantial flexibility for smarter charging.
- AI can translate complex utility tariffs into practical charging recommendations at scale.
- Future charging systems can coordinate cost, emissions, grid needs, and driver convenience.