https://doi.org/10.1038/s44460-026-00032-4

Sensing meets physics-aware artificial intelligence for empowering smart batteries

Yunhong Che, Jiaqiang Huang, Xiaosong Hu & Richard D. Braatz

Advanced sensing and physics-aware artificial intelligence are reshaping smart batteries with interpretable insights and non-destructive diagnostics. Yet, fragmented progress and case-specific solutions have hindered impact. Closing this gap requires systematic, closed-loop integration from sensing to physics-aware models to translate raw observations into interpretable predictions for safer, longer-lasting, and smarter energy storage systems.

Batteries, serving as the main energy storage system, power a wide variety of devices from portable electronics to electric transportation and robotics[1,2]. Batteries are multi-physics systems that incorporate coupling and complex reactions. An undetected defect can cascade into rapid capacity loss or catastrophic thermal runaway, with consequences ranging from costly downtime to public safety hazards. These risks are growing as battery systems become larger, more complex, and more widely deployed in critical infrastructure. Thus, battery management has turned from reactive to predictive[3,4] and smart batteries have become capable of interpreting internal mechanisms and forecasting failures through advanced sensing and artificial intelligence (AI) to facilitate better use and enable additional functions such as healing, smart charging, and adaptive switching[5]. Beyond separate advancement of smart sensing and advanced AI models, here we advocate a systematic and closed-loop framework design with both forward and backward optimizations to integrate smart sensing with physics-aware modelling, enabling predictive and interpretable health and safety management.

Advanced sensing for condition monitoring

Beginning with current, voltage, and temperature sensors for measurements of battery operational behaviours via a battery management system, to external impedance measurement via electrochemical impedance spectroscopy technologies and mechanical description through pressure detection, battery characterization is developing towards multidimensional descriptions of electro-mechanical-thermal-ageing conditions. However, external monitoring is limited in both spatial and temporal characterization, and microscopic variations inside batteries are unmeasurable with conventional sensors, which leads to unexpected hazards without timely observation[6]. To this end, advances in sensing technologies have opened a window into the non-destructive measurement of battery internal conditions. Distributed potential sensors and embedded temperature sensors detect overpotentials and thermal conditions in real time, while additional pressure, strain, and gas sensors are implemented to enhance battery degradation and safety diagnosis by gathering additional key features. For example, volume changes in electrodes detected by pressure or strain sensing can be used to effectively track the formation of the solid electrolyte interface and gas generation[7,8], whereas acoustic and fibre-optic sensors enable internal temperature and strain gradients monitoring and reconstruction to interpret critical events such as material phase transitions, gas evolution, and crack events[5,8]. With new sensing insights, multi-physics interactions are trackable as they unfold, capturing high-resolution, multidimensional signals tightly linked to degradation and safety-critical events, enabling faster diagnosis and operando health and safety management of batteries[9–12]. Yet this information richness comes at the cost of the fabrication of different sensors and implementations – that might even contain redundancy – and is overwhelming for conventional analytical models that are not able to interpret the coupling data. The result is a paradox: the ability to observe has increased, but the ability to manage and interpret these observations has not kept pace.

Physics-aware diagnostic modelling

Machine learning modelling typically links signal observations to systems' health and safety diagnoses. Due to the poor physical interpretability and extensive label requirement for conventional data-driven models, physics-aware AI models are built to embed physical laws or features into modelling, which offers a compelling route toward interpretable and generalizable predictions[13,14]. Frameworks such as physics-informed neural networks, hybrid mechanistic–data-driven models, and physics-constrained learning (Fig. 1a) have shown strong performance in scenarios with limited data, unfamiliar chemistries, or unseen working conditions[3,4]. These models have potential for AI-based battery design and management. However, most implementations still rely on idealized, low-dimensional inputs such as voltage and temperature from controlled experiments, while high noise still largely deteriorates reliability. Active perturbations, such as pulses and dynamic impedance, provide more insight into mechanisms to feed machine learning models together with advanced sensor technologies[15]. Even if these physical features can be used to deeply understand internal mechanisms, they are still mostly used as direct features, like conventional electric information. As a result, they are still left aside and lack comprehensive integration that could be reached, for example, by using additional information to increase the observability of the models and to constrain the explicit physical interpretations in the physics-aware models for earlier and more reliable detection of degradation and safety risks under practical applications. In addition, systematic model development for wide usage considering multi-physics coupling remains unsolved, and models are still designed specifically for desired tasks (for example, in battery properties emulations or predictions).

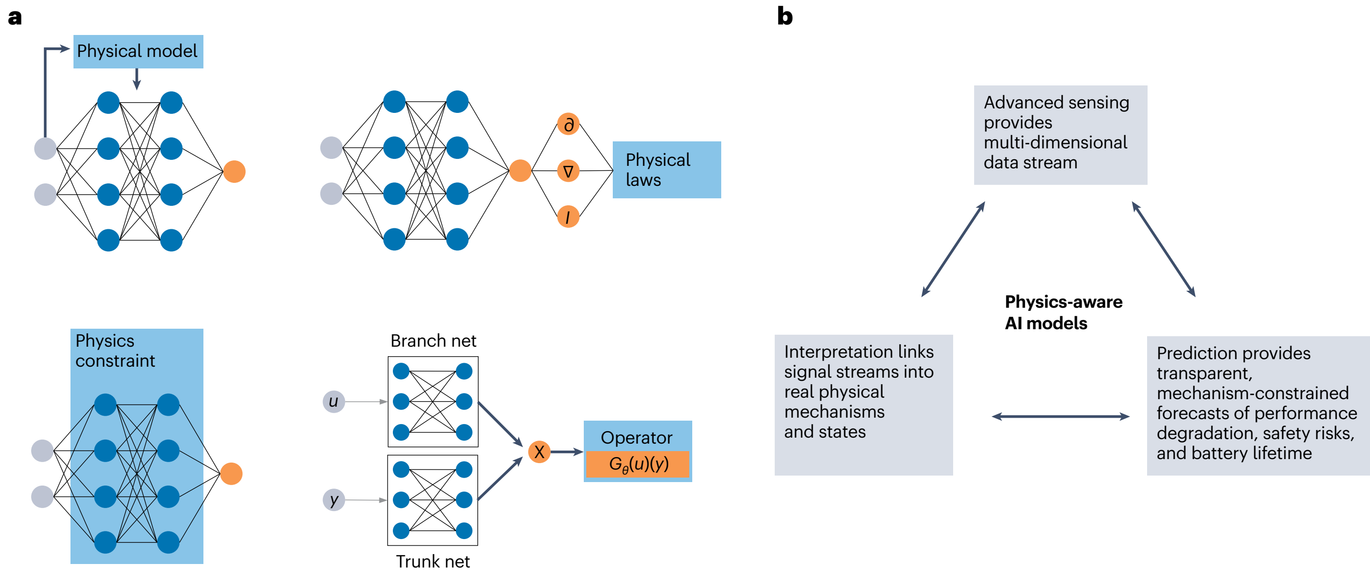

Fig. 1 | Routine of integrating advanced sensors and physics-aware AI models. a, Physics-aware AI models for battery modelling. **b**, Systematic integration of advanced sensors and physics-aware AI models for smart batteries.

Despite the separate advancements discussed above, the trajectory of smart battery development is still shaped by intertwined bottlenecks. Although better predictions with critical internal characteristic features are obtained[7,12], they still suffer from domain discrepancies, and similar accuracy can be reached with conventional signals[3,4]. In addition, several sensing methods achieve a similar detection purpose while lacking a systematic design with backward inspiration of physics-aware models considering both spatial and temporal properties. Therefore, a closed-loop reasoning that combines smart sensing with physics-aware AI models is still missing. Key information obtained from advanced sensors fails to continuously support physics-aware AI models updating, whilst predictive models do not guide the optimal construction and placement of these sensors. Furthermore, data secrecy and scarcity issues pose high challenges to the development of both an optimal smart sensing strategy and the advanced physics-aware AI models. Together, these limitations constrain our ability to transform raw observations into mechanism-aware predictions that adapt to evolving battery conditions.

Closed-loop integration

A unified, systematic, and interdisciplinary framework of sensing–interpretation–simulation–prediction (SISP) that tightly couples advanced sensing with physics-aware AI models in an adaptive loop with both forward and backward integrations is needed (Fig. 1b). In the forward loop, multimodal data are gathered from advanced sensors such as optical, acoustic, strain, and electrochemical probes under realistic operating conditions to track key mechanistic information of battery reactions. Before data-driven modelling, comprehensive interpretation links these signal streams into real physical mechanisms and states, using domain knowledge and physical models, guiding the optimal feature constructions. Then, physics-aware AI models that couple multi-physics dynamics are expected to be built for simulation and prediction, aiming at reconstructing hidden multi-physics interactions and exploring hypothetical scenarios, enabling the testing of the consequences of potential degradation and safety pathways before they unfold. In addition, underlying unknown physical relationships could potentially be discovered by advanced physics-aware AI models, such as using the physics-informed neural operators to learn the operator mappings between input sensing signals and output properties. Finally, interpretable prediction provides transparent, mechanism-constrained forecasts of performance degradation, safety risks, and remaining useful life to guide optimal operation and maintenance, while also feeding back to refine sensing priorities. The physics-aware AI models act as the bridge to collect each part of this framework, taking critical mechanistic features from smart sensors, facilitating mechanism interpretation, and enabling physics-aware modelling and predictions.

Beyond the forward loop from sensing to predictions, we emphasize the importance of backward optimization for both smart sensing and physics-aware modelling. In SISP, the comprehensive analysis between the mechanisms and sensing observations can be used to backwardly guide sensor implementations and avoid redundancies. The physics-aware model not only simulates the battery performance but further fulfils the mechanisms with the external observations, such as the potential to find new coupling mechanism principles. Furthermore, these physics-aware models guide the implementation of smart sensors according to the observability and physics reconstruction capabilities. Finally, predictions also turn back to guide the physics-aware model construction and enhance the interpretation of the mechanisms incorporating evolution in the future safety and degradation pathways, which closes the whole loop in the end. Together, these bidirectional interactions enable battery systems to learn from every sensing event, adapt to evolving conditions, and progressively improve both accuracy and interpretability.

Systematic construction of both the inner loop (within either advanced sensing or physics-aware modelling) and the inter loop between the two is critical to realizing the vision of smart batteries.

Within the inner loop, sensing needs go beyond deploying new probes for targeted mechanisms. It requires a multi-dimensional, multilevel design that captures battery behaviour across scales from material properties to full systems while minimizing redundancy by considering the systematic implementations instead of individual purposes. In parallel, the development of physics-aware AI models also needs inner loop construction by embedding multi-physics constraints and addressing system-level inconsistencies, to deliver more faithful and interpretable representations of battery dynamics. Extending outward, the inter loop of systematic co-development of sensing and physics-aware AI models is important to establish the critical bridge uniting perception and prediction. In this bidirectional pathway, sensing informs model construction and provides more observations for physical constraints, while predictive insights feed back to interpret the coupled mechanisms of the multi-dimensional perceptions and optimize the sensor deployments. Together, these mutually reinforcing loops pave the way for batteries that operate with greater safety, intelligence, and interpretability.

Pathways for implementations

This framework holds promise across diverse battery applications throughout their life span, where safety, longevity, and performance are paramount. In electric vehicles and grid energy storage, the dominant in-service applications, advanced sensing can capture early signatures of internal safety hazards under real-world operations, while revealing cell-to-cell heterogeneity and hidden degradation patterns. Physics-aware simulations predict defect evolution under realistic conditions and provide mechanism-informed forecasts of safety risks and capacity fade, enabling proactive maintenance and adaptive control to enhance both performance and lifetime. For batteries in specific application scenarios, such as spacecraft, robotics, or submarines, model boundaries of applicability, limited by extreme conditions like large current rates, high or low temperatures, and high mechanical stress, are expected to be extended through machine learning. Complex coupling stress identification to inform robust design and operational safeguards also has great potential in large AI data centres. Insights from SISP also guide end-of-life decisions, including cell matching for second-life deployment and recycling, while real-time sensing on production lines enables early defect detection and rapid intervention, improving yield and reliability.

To realize full potential, coordinated efforts are essential. First, the systematic construction of a real-time, closed-loop SISP system requires deliberate integration of sensing, knowledge of mechanisms interpretation, physics-aware modelling, and predictive diagnosis into a systematic architecture. This involves co-designing sensors and embedded hardware with physical AI software, enabling continuous adaptation to evolving battery conditions. Demonstrating these adaptive feedback loops in operational battery platforms will be a critical step toward validating SISP's robustness and scalability. Second, deep interdisciplinary convergence with systematic engineering from detection and perception to interpretation and prediction, which incorporates collaboration among different disciplines traditionally operated in parallel, needs to be fully considered. Establishing cross-disciplinary research hubs, joint training programmes, and shared experimental testbeds will accelerate both conceptual and practical advancements. Project and funding opportunities are recommended to consider collaborative research that incorporates and cultivates young researchers with cross-disciplinary skills and experts and groups with different backgrounds to facilitate co-development and practical deployment. Third, enabling collaborative model development under strict data protection makes it practical. Large and high-quality datasets linking sensor signals to degradation failures often contain proprietary details about battery designs, operational profiles, failure modes, and even personal privacy and patents. To reconcile the need for data richness with confidentiality, emerging privacy-preserving strategies, such as federated learning, secure multiparty computation, and privacy-aware feature extraction, enable collaborative model development without exposing raw data. In parallel, standardized anonymization protocols and benchmark datasets curated by neutral consortia can promote transparency and comparability across institutions. Embedding these safeguards ensures that progress can be collective, secure, and sustainable.

Conclusions

In summary, advancing smart battery technologies demands more than incremental improvements in sensing or AI alone, rather it requires their systematic, closed-loop integration to enable highly advanced perception and prediction capabilities. We outlined the SISP framework with both inner and inter-systematic design as a concrete embodiment of this vision, enabling real-time, adaptive, and mechanism-driven insights into battery behaviour. By uniting interdisciplinary expertise, embedding continuous feedback between sensors and models, and safeguarding collaborative development through privacy-preserving data strategies, SISP offers a pathway to transform batteries from passive energy storage devices into intelligent, self-optimizing systems. Realizing this vision will not only enhance safety, longevity, and performance but also set a new paradigm for interpretable and trustworthy energy storage in the next generation of applications.

Yunhong Che [1,2], **Jiaqiang Huang** [3], **Xiaosong Hu** [4] ✉ & **Richard D. Braatz** [1] ✉

[1]Department of Chemical Engineering, Massachusetts Institute of Technology, Cambridge, MA, USA. [2]Department of Energy, Aalborg University, Aalborg, Denmark. [3]Sustainable Energy and Environment Thrust and Guangzhou Municipal Key Laboratory of Materials Informatics, The Hong Kong University of Science and Technology, Guangzhou, Guangdong, China. [4]College of Mechanical and Vehicle Engineering, Chongqing University, Chongqing, Chongqing, China.
✉e-mail: xiaosonghu@ieee.org; braatz@mit.edu

Published online: 23 February 2026

References

1. Huang, J., Boles, S. T. & Tarascon, J.-M. *Nat. Sustain.* **5**, 194–204 (2022).
2. Shi, Y. & Pikul, J. H. *Sci. Robot.* **10**, eadr6125 (2025).
3. Che, Y. et al. *Joule* **9**, 102010 (2025).
4. Wang, F., Zhai, Z., Zhao, Z., Di, Y. & Chen, X. *Nat. Commun.* **15**, 4332 (2024).
5. Meng, Q., Huang, Y., Li, L., Wu, F. & Chen, R. *Joule* **8**, 344–373 (2024).
6. Gervillié-Mouravieff, C., Bao, W., Steingart, D. A. & Meng, Y. S. *Nat. Rev. Electr. Eng.* **1**, 547–558 (2024).
7. Fan, J. et al. *Nature* **641**, 639–645 (2025).
8. Lu, Y. et al. *Energy Environ. Sci.* **16**, 2448–2463 (2023).
9. Huang, J. et al. *Nat. Energy* **5**, 674–683 (2020).
10. Merryweather, A. J., Schnedermann, C., Jacquet, Q., Grey, C. P. & Rao, A. *Nature* **594**, 522–528 (2021).
11. Olgo, A. et al. *Nat. Commun.* **15**, 10258 (2024).
12. Zhang, T., Tan, R., Zhu, P., Zhang, T.-Y. & Huang, J. *ACS Energy Lett.* **10**, 862–871 (2025).
13. Karniadakis, G. E. et al. *Nat. Rev. Phys.* **3**, 422–440 (2021).
14. Yu, R. & Wang, R. *Proc. Natl Acad. Sci.* **121**, 2311808121 (2024).
15. Tao, S. et al. *Energy Environ. Sci.* **18**, 7413–7426 (2025).

Acknowledgements
This work was supported by the Novo Nordisk Foundation under grant NNF24OC0088261 and the National Natural Science Foundation of China under grants U23A20327, 52402465, and 92372109.

Author contributions
Y.C., X.H., and R.D.B. conceived the idea. Y.C. and J.H. conducted the paper search and prepared the first draft. All authors contributed substantially to the discussion of the content.

Competing interests
The authors declare no competing interests.

Additional information
Peer review information Nature Sensors thanks Shengyu Tao and the other anonymous reviewer(s) for their contribution to the peer review of this work.