Battery Health Monitoring Using Unsupervised AI

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PROJECT PROFILE
Topic: Safety and Reliability
Strategic Pathway: Energy Storage
Project start and finish: FY2026-Ongoing

PROBLEM

❑**Goal:** Estimate long-term SOH for grid-scale batteries under variable DoD — without failure labels.

❑**Why hard:** Competing degradation mechanisms (LLI, LAM, calendar aging) produce overlapping capacity-fade signatures; diagnostic signals are split across asynchronous modalities (cycling, dV/dQ, EIS) and rarely fused.

❑**Why now:** DOE-OE targets multi-decade grid storage; field data is abundant b ut labeled cycle-to-failure data is not.

❑**Gap:** Coulomb counting + Kalman filters drift on long-term SOH; supervised ML needs labeled failure data that doesn't transfer across operating conditions.

APPROACH

❑ **Architecture:** Multimodal autoencoder with a shared latent space that fuses cycling time-series, dV/dQ, EIS, and scalar diagnostics — modalities sampled at different rates.

❑ **Training:** Early-life "healthy" data only; no failure labels, no condition-specific tuning.

❑ **Detection:** Reconstruction error rises as later-life measurements deviate from the learned healthy baseline.

❑ **Attribution:** Identify which modality carries the strongest degradation signal at each life stage.

❑ **Operational output:** Map reconstruction error to a calibrated SOH score for field use.

Early life healthy data → Multimodal Autoencoder → Reconstruction error → SOH score

RESULTS

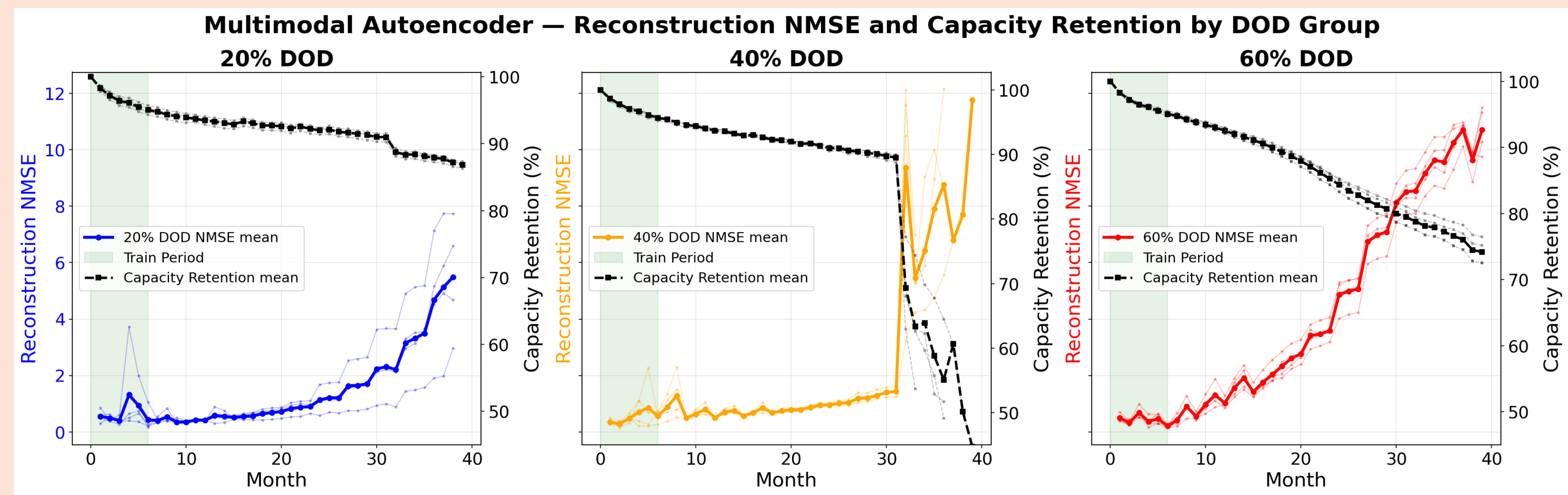

Fig. 1. Multimodal reconstruction NMSE and capacity retention across DOD groups. The model consistently tracks capacity degradation, capturing physically distinct trajectories.

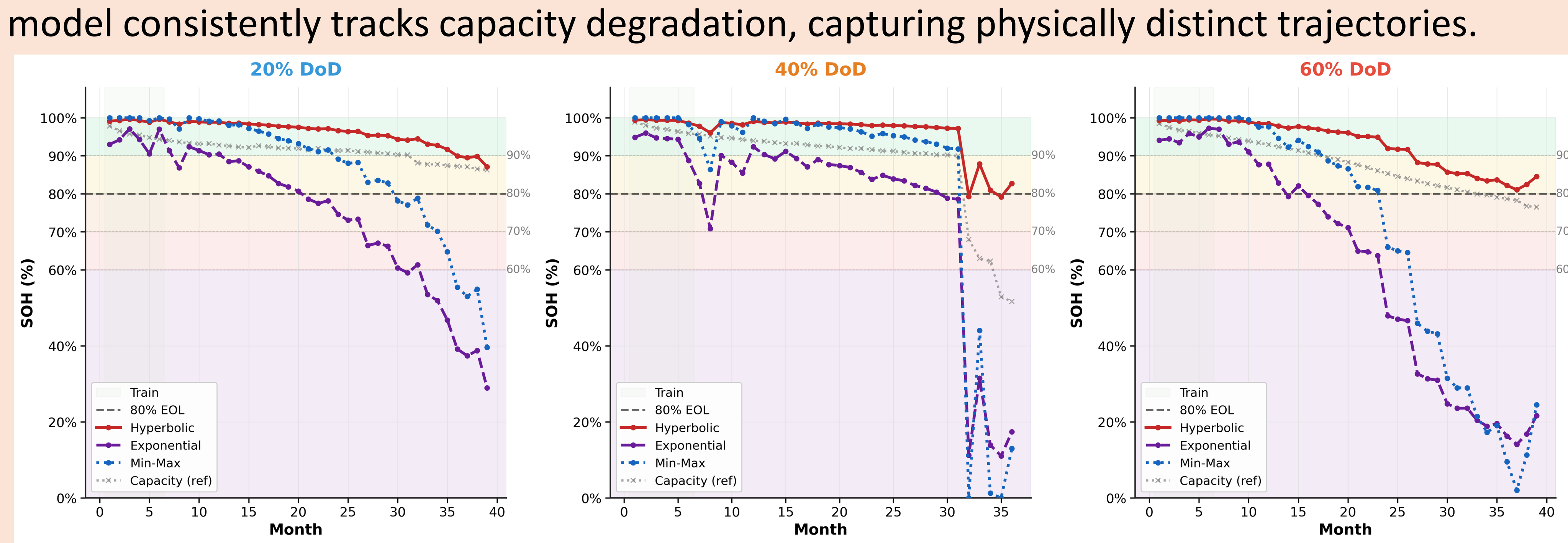

Fig. 2. SOH model from Reconstruction error

CONCLUSION AND IMPACT

❑Single unsupervised model successfully captures three physically distinct degradation trajectories, no labels, no condition-specific tuning

❑Reconstruction error consistently rises with capacity fade, confirming it as a viable degradation proxy across all DoD groups

❑SOH mapping demonstrates the feasibility of converting reconstruction error into an actionable health score — though current estimates show over/underestimation that requires further calibration

FUTURE DIRECTION

❑ SOH calibration requires refinement

❑ Validate against larger, multi-chemistry datasets.

❑ Extend from degradation detection to quantitative Remaining Useful Life (RUL) prediction using trajectory forecasting from the learned latent space

❑ Complementary physics-based degradation modeling (PyBaMM, P2D) within the group provides mechanistic interpretation; future work will fuse physics-derived features with the learned latent space for hybrid SOH estimation.

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