Detecting Battery Degradation Trajectories Using Multimodal Autoencoder Reconstruction Error

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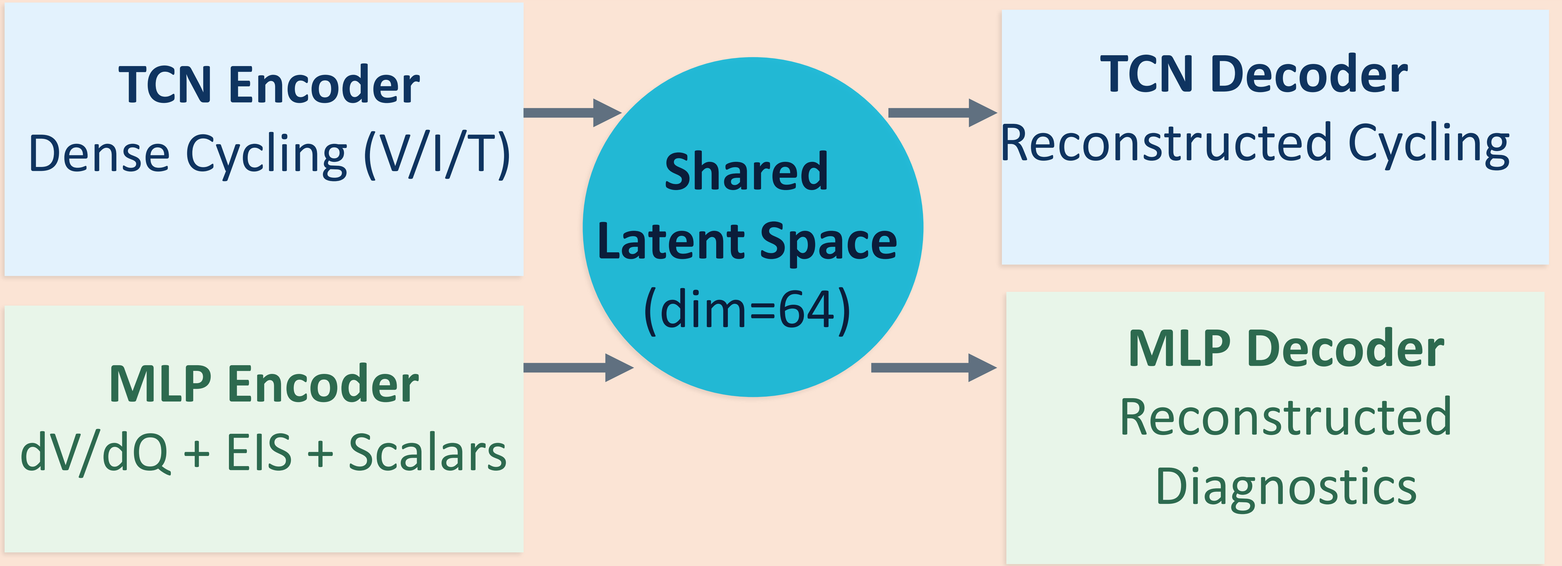
OBJECTIVE

- ❑ Monitor battery cell degradation over its full lifetime
- ❑ Detect degradation using AI, no labels required
- ❑ Generalize across operating conditions, no tuning needed

METHODOLOGY

- ❑ **Dual-Encoder Architecture**:
  - ❑ **TCN** encodes cycling time-series (voltage, current, temperature)
  - ❑ **MLP** encodes electrochemical diagnostics (dV/dQ, EIS, scalar metrics)
- ❑ **Shared Latent Space**: Both encoders compressed into a 64-dimensional representation
- ❑ **Training**: Trained only on healthy early-life data (months 1–6)
- ❑ **Testing**: Evaluated on later measurements across the full cell lifetime
- ❑ **Degradation Signal**: Normalized reconstruction error (NMSE) — rises as cell health declines
- ❑ **Analysis**: Degradation trends tracked across depth-of-discharge (DoD) groups

MODEL ARCHITECTURE



375,644 parameters | Batch size: 8 | Latent dim: 64 | | Trained on CPU (16 GB RAM)

DATASET

CELLS	DURATION	DOD (4cells each)
12 NCA cells	39 months	20% 40% 60%
DUTY CYCLE	**TRAIN PERIOD**	**TEST PERIOD**
Peak Shaving	Months 1–6	Months 7–39

- ❑ **Cycling:** Voltage, current, temperature — first peak-shaving cycle each month, truncated to 512 timesteps
- ❑ **dV/dQ:** 200-dim interpolated differential voltage curve — monthly cadence
- ❑ **EIS:** 300-dim impedance vector (real + imaginary × 50 frequencies × 3 SOC points) quarterly, forward-filled
- ❑ **Scalars:** 5 features — discharge capacity, energy, coulombic efficiency, average voltage, end voltage

RESULTS

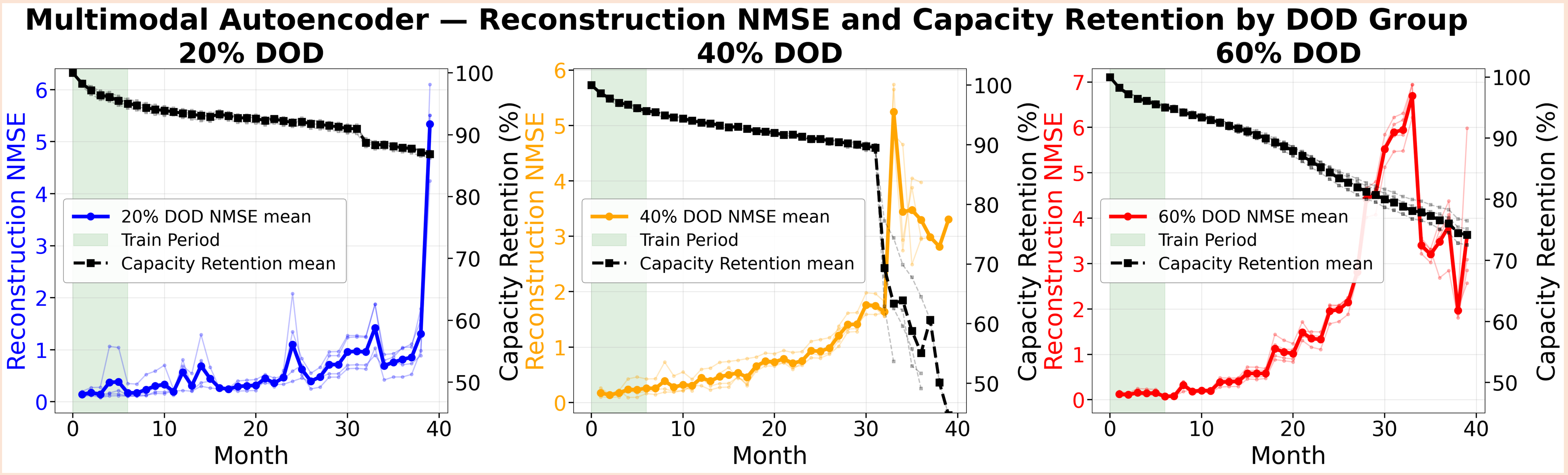


Fig. 1. Multimodal reconstruction NMSE and capacity retention across DOD groups. The model consistently tracks capacity degradation, capturing physically distinct trajectories.

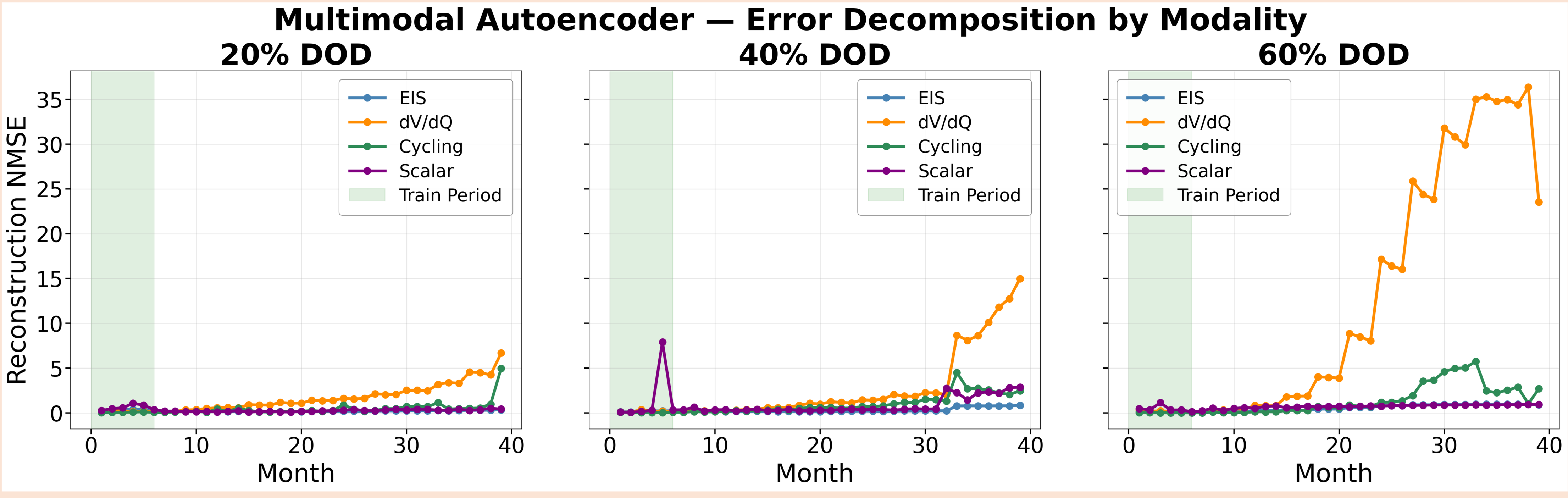


Fig. 2. Reconstruction error decomposition by modality for multimodal autoencoder

RESULTS — DOD TRAJECTORIES

- ❑ **20% DOD — Gradual Fade**
  NMSE rises steadily with slow capacity fade; continuous electrochemical evolution captured from early life.
- ❑ **40% DOD — Sudden Failure**
  Sharp NMSE spike aligns with abrupt capacity drop at **~month 31**.
- ❑ **60% DOD — Accelerated Aging**
  High NMSE from the earliest months signals rapid degradation under severe mechanical stress.

CONCLUSION AND FUTURE WORK

✅ **Key Findings:**

- ❑ **Single model, three trajectories:** Captures physically distinct degradation patterns across all DoD groups — **no condition-specific tuning**
- ❑ **Dominant indicator: dV/dQ** identified as the strongest degradation signal across all conditions (via per-modality error decomposition)
- ❑ **Physically consistent onset:** Trajectory timing follows stress ordering — 60% DoD shows **earlier and steeper** error rise than lower-stress conditions

Future Work:

- ❑ Per-cell **dV/dQ analysis** across all 12 cells
- ❑ Replace **EIS with DC internal resistance** → enable fully monthly multimodal updates
- ❑ Extend to additional **duty cycles and chemistries.**

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