# 1. Introduction

The rapid global electrification of transportation and expansion of grid-scale energy storage have thrust lithium-ion batteries to the forefront of modern power systems. In 2024, worldwide electric vehicle (EV) sales surpassed 17 million units—a year-on-year increase of over 25%—and grid-tied storage installations continue to grow at an annual rate exceeding 20%. As battery packs operate across ever-widening temperature, charge/discharge, and duty-cycle regimes, accurate real-time estimation of the battery’s State of Health (SOH) becomes paramount for:  
- Ensuring safety, by detecting accelerated aging or internal faults early;  
- Maximizing usable lifetime, through optimized charge–discharge strategies;  
- Enabling second-life applications, by quantifying residual capacity for repurposing.

# 2. Fundamentals

2.1 SOH Definition & Calculation  
Identify full-discharge intervals (Schedule\_Step\_ID ∈ [5,7]) to compute initial capacity C\_init and subsequent capacities C\_curr. Define SOH = C\_curr / C\_init.

2.2 Key Input Features  
- Current (C-rate): Governs lithium flux and side-reaction rates.  
- Voltage (V): Reflects internal resistance growth and polarization.  
- Temperature (T): Modulates reaction kinetics and degradation mechanisms.  
- Cumulative Throughput (Q\_sum/EFC): Equivalent full cycles, provides a global “aging clock.”

2.3 Incremental Learning Methods  
- Elastic Weight Consolidation (EWC): Penalizes changes to parameters deemed important.  
- Learning without Forgetting (LwF): Uses soft-label distillation to retain prior performance.  
- Naïve Fine-Tuning & Replay: Baseline approaches for comparison.

# 3. Methodology

3.1 Data Preparation  
- Resample raw time series to 10 min intervals (optimal trade-off).  
- Compute Δt, per-step charge Q = I·Δt, absolute throughput |Q|, and cumulative Q\_sum for EFC.  
- Handle outliers and interpolate missing timestamps.

3.2 Data Splits  
Joint Training: 14 cells (IDs 03–29, excluding 17) split 11:3 by ageing regime; C17 held out as final test.  
Incremental Stages:  
 1. Base (normal): train {03,05,07,27}, val {01}  
 2. Update 1 (fast): fine-tune {21,23,25}, val {19}  
 3. Update 2 (faster): fine-tune {11,09,15,29}, val {13}  
 Final testing on full C17 and incremental splits for forward/backward transfer.

3.3 Hyperparameter Optimization  
Stage 1 (Network & Regularization): window 6–1008 steps, hidden size {32,64,128,256}, layers {2–5}, dropout [0.0–0.5], weight decay [0–1e–4], batch size {16–128}.  
Stage 2 (Preprocessing & Learning Rate): Scaler {Standard, MinMax, Robust}, initial LR [1e–5–1e–3], Scheduler {StepLR, CosineAnnealingLR, ReduceLROnPlateau} with tuned parameters.

# 4. Results

- Joint vs. Naïve Fine-Tuning: Joint MAE ≈ 0.0057; naïve fine-tuning exhibits significant forgetting.  
- EWC & LwF Performance: Increasing λ reduces forgetting, approaches joint baseline.  
- Final Test on C17: RMSE ≈ 7.2×10⁻³, MAE ≈ 5.7×10⁻³, R² ≈ 0.993.  
- Smoothness Analysis: Effects of Scaler and LR schedule on high-frequency noise suppression.

# 5. Discussion

- Adaptivity: EWC+LwF preserve prior ageing patterns while incorporating new regimes.  
- Feature & Preprocessing Impact: RobustScaler and Q\_sum yield globally monotonic, locally smooth predictions.  
- Deployment: Selected LSTM architecture and update routines meet real-time constraints on automotive MCU/SoC.

# 6. Conclusion

We introduce an incremental-learning LSTM framework for SOH estimation that integrates new cycling data without catastrophic forgetting. By fusing physical features (C, V, T, Q\_sum) and employing dual regularization (EWC, LwF), our model achieves high accuracy (MAE≈0.0057, R²≈0.993) and smooth, reliable degradation curves within onboard resource limits.

# 7. Outlook

Future work will explore extreme-condition generalization (high/low temperature, ultra-high C-rates), integrate second-order smoothness regularizers, and investigate hybrid Transformer-LSTM architectures for enhanced incremental adaptation.