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Real-time degradation modeling for automotive PEMFC stacks: a multi-scale fusion network validated on an industrial 215-channel system

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Background & Motivation

Why PEMFC Degradation Prediction Matters

- PEMFCs offer zero emissions, rapid refueling (3–5 min), and excellent cold-start performance — ideal for heavy-duty trucks and cold-chain logistics.
- Under real automotive conditions, degradation is 3–5× faster than in lab tests, dramatically increasing lifecycle costs.
- Complex failure mechanisms: catalyst detachment, membrane degradation, bipolar plate corrosion driven by dynamic loads and stop/start cycles.

Three Key Limitations in Existing Methods

Stack Scale

Most studies use <50 cells; industrial >200-cell stacks show up to 30% variation in degradation rates due to multi-physics coupling.

Condition Bias

Simplified lab protocols (constant/cyclic loads) fail to reflect dynamic load transients and environmental variability.

Noise Coupling

Inlet-side sensor noise is 20–40% higher than outlet; conventional denoising loses up to 15% of effective signal information.

Proposed Methodology: MBFNet

Multi-scale Bidirectional Fusion Network (MBFNet) — Four Core Contributions

01

Industrial GHE Co-simulation Platform

215-channel, 95 kW PEMFC stack tested under accelerated East China climatic conditions. 327 hours of aging data with synchronized flow-field and electrochemical monitoring.

02

Channel-Joint Adaptive NCT Algorithm

Noise Correlation Threshold algorithm dynamically constructs spatio-temporal noise thresholds via dual-channel coherence analysis — no prior physical modeling required.

03

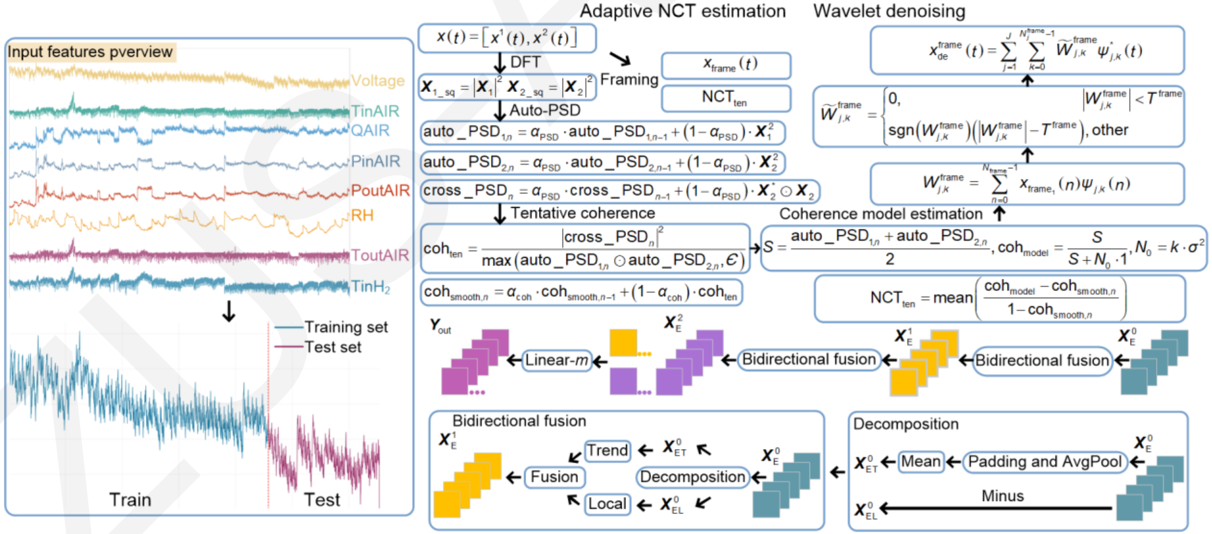
Multi-scale Decomposition Module

Decomposes voltage sequences into 5 temporal scales (I, I/2, I/4, I/8, I/16), disentangling short-term voltage recovery transients from long-term irreversible aging trends.

04

Lightweight Bidirectional Fusion Module

Integrates stack-level global degradation trends with cell-level local anomalies via parameter-efficient projections. Linear computational complexity enables GPU-parallel inference.



Flowchart of the proposed multi-scale bidirectional fusion network

Dataset & Experimental Setup

Industrial-Grade GHE Co-simulation Platform

Stack Configuration

- 215 series-connected cell pairs
- Rated power: 95 kW
- Voltage monitoring per paired channel

Data Collection

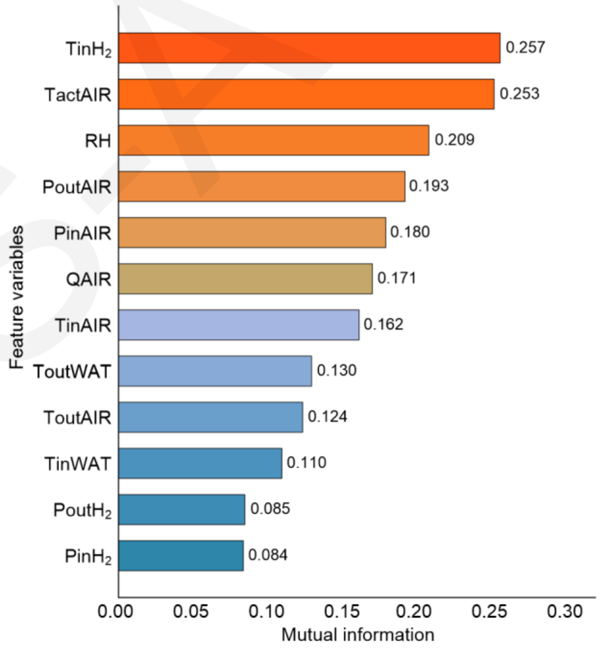
- 327 hours of accelerated aging
- 5 Hz raw → 0.2 Hz downsampled
- Spatio-temporal alignment <5 ms

Operating Conditions

- East China climatic scenarios
- Nominal current: 330 ± 5 A (~72%)
- Dynamic load + start/stop cycles

Degradation Profile

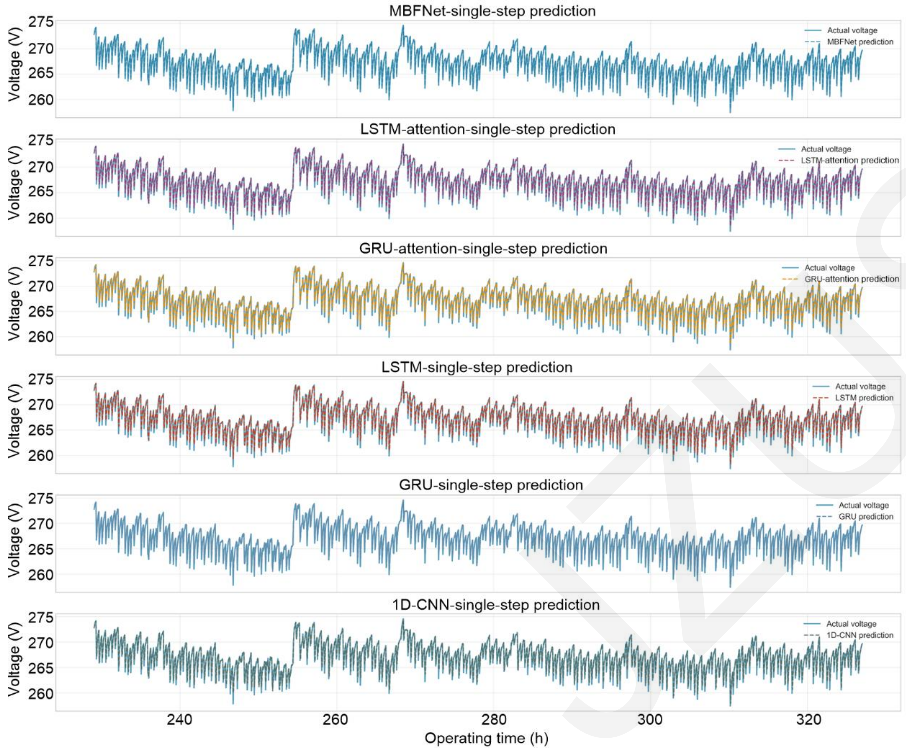
- Stack V: 280.6 → 266.3 V (−14.3 V)
- Rate: 203.42 μV/(cell·h)
- EOL: −10.5% of initial peak voltage



Feature Selection: 7 variables with MI > 0.15 selected — $TinH_2$, TactAIR, ToutAIR, RH, PinAIR, PoutAIR, QAIR — reducing input dimensionality by 42% while preserving physically meaningful degradation signals.

Experimental Results & Performance Comparison

MBFNet outperforms all baselines on accuracy, efficiency, and physical interpretability



Single-step prediction performance

Model	R^2	E_{RMS}	E_{MA}	E_{MAP} (%)	Train (min)	Para (×10[4])
MBFNet (ours)	0.9654	0.0180	0.0123	0.3002	15.2	2.4
LSTM-attention	0.9482	0.0221	0.0157	0.4125	21.7	3.8
GRU-attention	0.9365	0.0253	0.0179	0.4983	18.9	3.6
LSTM	0.9124	0.0317	0.0214	0.6541	11.3	3.2
GRU	0.9038	0.0348	0.0236	0.7329	9.8	2.9
1D-CNN	0.8741	0.0425	0.0291	0.9257	4.5	1.7

Voltage recovery intervals predictionperformance analysis

Model	R^2	E_{MAP}	Correlation	Recovery error
MBFNet (ours)	0.8281	0.45%	0.91	1.12×
GRU-attention	0.4489	0.76%	0.67	1.84×
1D-CNN	0.3025	1.25%	0.55	3.02×

Conclusions & Future Work

Key Conclusions

1. First 215-channel PEMFC GHE co-simulation platform established, significantly reducing data bias from laboratory conditions.

2. NCT algorithm achieves dynamic multi-physics noise suppression without prior physical modeling.

3. Multi-scale decomposition effectively decouples voltage recovery and long-term aging — aligned with physical degradation mechanisms.

4. MBFNet yields 18.5% lower single-step error than LSTM-Attention, along with 24.5% and 55.2% reductions in multi-step error over LSTM-Attention and 1D-CNN.

5. Lightweight design (24K parameters, <15 ms latency) satisfies automotive ECU constraints.

Future Work

- Integrate online diagnostic data to enhance model generalization across diverse vehicles.
- Develop adaptive parameter adjustment mechanisms for different road and climate conditions.
- Validate robustness through real-world commercial vehicle deployment.

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