Robust Health Indicator Extraction and RUL Prediction for PEMFCs under Highly Dynamic Industrial Conditions

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Abstract

Proton Exchange Membrane Fuel Cells (PEMFCs) are increasingly deployed in clean energy systems, such as GEH2 hydrogen generators, where they operate under highly dynamic and unpredictable load conditions. Accurate prediction of their Remaining Useful Life (RUL) is essential for ensuring reliable, cost-effective, and proactive maintenance strategies. However, conventional voltage-based Health Indicators (HIs) are highly sensitive to power fluctuations and fail to provide consistent degradation trends in real-world industrial scenarios, particularly when system usage varies significantly across different clients, as in the GEH2 case. In this paper, we propose a scalable two-stage framework for RUL prediction of PEMFCs operating under such conditions. First, we introduce a machine learning-based method to extract a degradation-specific Health Indicator directly from voltage measurements, effectively filtering out transient operational effects. Second, we develop a hybrid deep learning architecture that combines Transformer networks and Gated Recurrent Units (GRUs) to model temporal dependencies and provide accurate RUL predictions under dynamic conditions. The proposed approach is validated on a real-world industrial dataset collected from three PEMFC stacks deployed in GEH2 systems operating under highly variable conditions. Comparative results show that our method consistently outperforms baseline machine learning and deep learning models, achieving superior accuracy, robustness, and generalization across diverse mission profiles.

1. Introduction

As a key technology in clean energy conversion, fuel cells based on proton exchange membranes offer a compelling combination of high efficiency, low environmental impact, and flexibility across a wide range of applications, from mobility solutions and portable electronics to stationary and emergency power systems (Wee, 2007). Their role is especially critical in electro-hydrogen generators such as the zero emission electro-hydrogen generator (GEH2) systems developed by EODev, where they produce electricity from hydrogen and oxygen, emitting only water as a byproduct. Despite these advantages, their broader industrial adoption remains challenged by issues related to long-term durability, frequent maintenance requirements, and gradual performance degradation.

To address these issues, accurate Remaining Useful Life (RUL) prediction is essential. It enables condition-based maintenance strategies that reduce operational costs, prevent unexpected failures, and improve system reliability (Hua, Zheng, Pahon, Péra, & Gao, 2021; J. Chen, Zhou, Lyu, & Lu, 2017). Yet, developing reliable prognostic models for PEMFCs remains challenging due to the complex and nonlinear nature of their degradation processes, which are influenced by interdependent factors such as current density, humidity, temperature, and load cycling (K. Li et al., 2024).

These challenges are particularly pronounced in real-world

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industrial settings, such as GEH2 systems, where PEMFCs operate under highly dynamic and user-dependent conditions. In these environments, the power demand fluctuates continuously, introducing transient effects that directly impact voltage measurements, the most commonly used signal for health assessment. As a result, traditional Health Indicators (HIs) based on voltage or power, though effective under static conditions, become unreliable in dynamic regimes. Transient load variations and changing environmental conditions can obscure true degradation patterns, making it difficult to distinguish between reversible operational effects and irreversible aging (Hua, Zheng, Pahon, & Péra, 2020; Yu et al., 2024; Zhang, Hou, Li, Chen, & Wang, 2025).

In this study, we introduce a two-stage, data-driven framework designed to overcome the limitations of traditional approaches by extracting a reliable, degradation-specific HI directly from voltage measurements. This HI is then used to accurately predict the Remaining Useful Life (RUL) of PEMFCs operating under dynamic and variable conditions. The effectiveness of the proposed method is demonstrated through validation on real-world industrial data collected from PEMFC stacks integrated into GEH2 systems, where it consistently captures degradation trends and outperforms existing prognostic models in highly dynamic environments.

The remainder of this paper is structured as follows: Section 2 provides an overview of related work on RUL prediction and Health Indicator extraction for PEMFCs, and highlights the specific contributions of this study. Section 3 presents the proposed methodology, covering both the HI extraction strategy and the hybrid deep learning model. Section 4 discusses the experimental results and comparative analysis. Finally, Section 5 concludes the paper.

2. BACKGROUND AND CONTRIBUTIONS

2.1. Related work and scientific contributions

In recent years, data-driven approaches have become increasingly popular for predicting the Remaining Useful Life (RUL) of PEMFCs, as they can model complex degradation behaviors without requiring detailed physical knowledge of the system.

Early research primarily employed conventional machine learning techniques, such as multi-kernel relevance vector machines (MK-RVM) optimized through Bayesian methods, demonstrating strong results under controlled conditions (Tian et al., 2023). Recurrent neural networks (RNNs), especially Long Short-Term Memory (LSTM) models, have been extensively utilized to capture temporal patterns in degradation data. For example, (Liu et al., 2019) implemented LSTM with Locally Weighted Scatterplot Smoothing (LOESS) and interval sampling to enhance prediction accuracy, while (Ma, Xu, Li, Yao, & Yang, 2021) combined adaptive LOWESS with bidirectional LSTM for real-time onboard RUL estimation in fuel cell vehicles.

More recently, Transformer-based models have attracted attention due to their capability to model long-range dependencies and handle non-stationary time series. (Zhou, Zeng, Zheng, Wang, & Zhou, 2025) proposed a Crossformer model with adaptive normalization, achieving significantly better performance than standard Transformers. Likewise, (Fu, Zhang, Xiao, & Zheng, 2024) employed a non-stationary Transformer coupled with discrete wavelet transform (DWT) for denoising, outperforming LSTM and Echo State Networks.

However, many of these approaches remain constrained to laboratory or simulated scenarios, which fail to reflect the complexities of real-world systems such as GEH2. In these environments, PEMFCs experience highly dynamic and user-driven power demands, causing transient fluctuations that directly impact voltage readings. Since voltage is the most commonly used Health Indicator (HI) for PEMFC prognostics, its sensitivity to operational variations makes it unreliable without proper compensation or filtering.

Several works have explored more robust HI formulations. (Z. Li, Zheng, & Outbib, 2019) proposed a data-driven strategy using sliding Linear Parameter-Varying (LPV) models to derive a virtual steady-state voltage, followed by RUL prediction using ensemble Echo State Networks. (Hua, Zheng, Pahon, Péra, & Gao, 2021) Introduced the Relative Power Loss Rate (RPLR), a dynamic HI better suited for varying mission profiles, coupled with a double-input Echo State Network for RUL prediction.

Building on RPLR, (Yang et al., 2025) used seasonal trend analysis and hybrid modeling on real-world fuel cell bus data. Similarly, (L. Chen et al., 2025) addressed voltage recovery effects using improved signal decomposition techniques and a hybrid deep learning model combining BiLSTM, CNN-attention mechanisms, and Kalman filtering for accurate RUL estimation.

Other approaches have focused on learning HIs directly from raw signals. (Wang, Li, Outbib, Dou, & Zhao, 2022) used symbolic regression and LSTM networks to extract robust HIs under dynamic conditions. (He, Liu, Sun, Mao, & Lu, 2022) developed a framework using autoencoders to learn latent degradation features from voltage data, which were then used in LSTM networks for RUL prediction.

Despite advances in data-driven prognostics, reliably extracting HIs for PEMFCs under real-world dynamic conditions remains a major challenge. Most existing methods are developed in controlled lab settings, which do not capture the complexity of industrial environments like GEH2 systems where power demand and operating conditions vary continuously. These fluctuations introduce significant variability into voltage signals, making it difficult to separate reversible operational effects from true degradation.

Additionally, many HI extraction approaches rely on complex multi-step processing or model-based compensation, which often lack generalizability and require extensive domain-specific tuning, limiting their practical applicability in industrial contexts. Furthermore, the joint integration of robust HI extraction with advanced deep learning architectures for Remaining Useful Life (RUL) prediction is still underexplored.

To address these gaps, this work contributes:

- A machine learning method to extract a degradation-specific HI directly from voltage data, effectively filtering out transient power demand fluctuations without complex preprocessing.
- A hybrid deep learning model combining Transformer networks and Gated Recurrent Units (GRUs) to capture temporal dependencies for accurate, robust RUL prediction under highly dynamic conditions.
- Validation on a real industrial dataset from PEMFC stacks in GEH2 systems, demonstrating practical applicability beyond simplified laboratory scenarios.
- Comprehensive benchmarking against state-of-the-art methods, showing superior accuracy, robustness, and generalization across variable operating profiles.

2.2. Data description and problem statement

Each GEH2 unit is equipped with an IoT-enabled data acquisition system that continuously collects a wide range of signals from distributed sensors and control units throughout the generator. These signals capture critical aspects of both the operating environment and system control, offering rich insights into the electrochemical behavior and degradation dynamics of the embedded PEMFC stacks.

Table 1 summarizes the key parameters used in this study. These include essential physical quantities such as stack current, air and hydrogen pressures, coolant temperatures, airflow, and stack voltage. Collectively, these variables represent the principal drivers of fuel cell performance and aging, and serve as the input features for health assessment and prognostics.

Table 1. Operating ranges of key PEMFC parameters.

Parameter	Description	Range
IFC	Stack current (A)	0 – 290
PHL	Hydrogen pressure (kPa)	50 – 282
FCO_TEMP	Outlet coolant temperature (°C)	15 – 69
FCI_TEMP	Inlet coolant temperature (°C)	16 – 61
PAFIC	Inlet air pressure (kPa)	80 – 206
QAF	Air flow rate (NL/min)	0 – 3600
VFC	Stack voltage (V)	0 – 400

Among these variables, stack voltage (VFC) is the most commonly monitored and widely used indicator of fuel cell health. However, in real-world industrial usage, it is heavily influenced by rapid fluctuations in power demand. As the current density changes instantaneously with varying load profiles, corresponding voltage responses exhibit high-frequency, irregular transients. As illustrated in Figure 1, the raw voltage signal of a typical PEMFC stack presents high variability, making it difficult to extract a clear long-term aging trajectory.

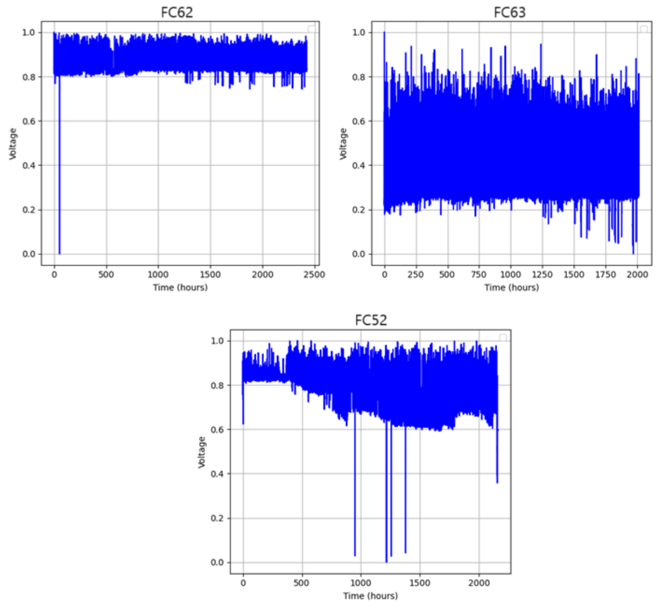

Figure 1. Evolution of overall stack voltage throughout the operating period.

Under static conditions, voltage decay is typically attributed to degradation alone. However, in dynamic environments, such as those encountered in GEH2 systems, voltage is also significantly shaped by mission profiles and load transients. Consequently, it becomes unsuitable to directly use voltage as a HI without accounting for these external effects. This challenge has only been partially addressed in the literature, with a limited number of studies proposing methods for robust HI extraction under such conditions (Hua, Zheng, Pahon, Péra, & Gao, 2021).

Given these complexities, there is a clear need for a more generalizable and practical method to derive degradation-specific HIs under real-world, dynamic operating conditions. This research addresses this gap through a twofold objective: *(1)* To develop a machine learning-based approach that extracts a robust Health Indicator from raw voltage signals, effectively separating true degradation effects from transient operational influences; *(2)* To design a deep learning framework that leverages this HI to accurately predict the Remaining Useful Life (RUL) of PEMFCs, even under non-stationary and highly dynamic operating profiles.

The next section introduces the proposed framework in detail.

3. PROPOSED METHODOLOGY

This section presents the complete methodology developed to perform robust Health Indicator (HI) extraction from voltage signals and RUL prediction under dynamic operating conditions. The proposed two-stage framework is illustrated in Figure 2, and detailed in the following subsections.

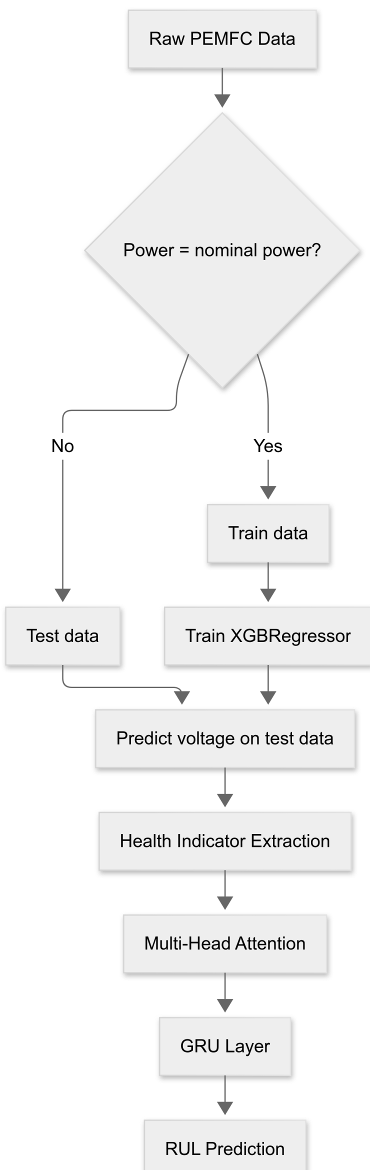

Figure 2. Overview of the proposed framework.

Health Indicator extraction via XGBRegressor

To isolate a voltage-based HI that tracks PEMFC degradation independently of load fluctuations, we fix the power output to a nominal value $P_{\text{out}}(t) = P_{\text{nom}}$. We then train an XGBRegressor to predict the true stack voltage $\mathrm{VFC}(t)$ whenever the PEMFC operates at this nominal power:

$$\widehat{VFC}_{\text{nom}}(t) \;=\; f_{\text{XGB}}\big(\text{Pout}(t),\, \mathbf{C}(t)\big), \tag{1}$$

where $P_{\text{out}}(t)$ is the output power, P_{nom} is the nominal output power, and $\mathbf{C}(t)$ is the vector of auxiliary operating conditions at time t:

$$\mathbf{C}(t) = \big[\mathrm{IFC}(t),\, \mathrm{FCI\_TEMP}(t),\, \mathrm{FCO\_TEMP}(t),\\ \mathrm{PAFIC}(t),\, \mathrm{PHL}(t),\, \mathrm{QAF}(t)\big] \tag{2}$$

with $\mathrm{IFC}(t)$ the stack current, $\mathrm{FCI\_TEMP}(t)$ the inlet coolant temperature, $\mathrm{FCO\_TEMP}(t)$ the outlet coolant temperature, $\mathrm{PAFIC}(t)$ the air pressure at the fuel cell inlet, $\mathrm{PHL}(t)$ the hydrogen pressure, and $\mathrm{QAF}(t)$ the fuel cell air flow.

During training, we restrict the dataset to those timestamps $\mathcal{T}$ at which $\text{Pout}(t) = P_{\text{nom}}$. The XGBRegressor model f_{XGB} is trained to minimize a regularized squared-error objective over the set $\mathcal{T}$:

$$\min_{f} \quad \sum_{t\in\mathcal{T}} \big(VFC(t) - f_k(P_{\text{out}}(t),\, \mathbf{C}(t))\big)^2 \;+\; \Omega[f_k], \tag{3}$$

where f_k is the prediction function of tree k and Ω is a regularization that penalizes the regression tree functions and is defined as follows:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda\|w\|^2, \tag{4}$$

where T is the total number of leaves in the tree, w is the leaf weights, and γ and λ are hyperparameters that control the regularization strength. Hyperparameters such as learning rate, maximum tree depth, number of estimators, and subsample ratio were tuned using GridSearchCV for each PEMFC to achieve a better balance between bias and variance. The estimated hyperparameter values are presented in Table 2.

PEMFC ID	Learning Rate	Max Depth	# Estimators	Subsample
PEMFC62	0.01	6	500	0.8
PEMFC63	0.10	3	100	1.0
PEFMC52	0.05	3	500	0.8

Table 2. Estimated hyperparameters for the XGBRegressor per PEMFC.

To extract a robust voltage-based Health HI, the XGBRegressor is trained to predict the stack voltage under nominal power conditions. The model takes as input the output power and a set of auxiliary operating variables (stack current, inlet/outlet coolant temperatures, air and hydrogen pressures, and air flow) and is trained only on timestamps where the output power equals the nominal value. The objective function minimizes a regularized squared error across these samples, while hyperparameters, including learning rate, tree depth, number of estimators, and subsampling ratio, are optimized via GridSearchCV to balance bias and variance. The trained model is then used to estimate the HI at all operating points, providing a degradation signal that is largely independent of transient load fluctuations and suitable as input for the Transformer-GRU RUL predictor.

After training, the voltage-based HI is given by the following:

$$\mathrm{HI}(t) \;=\; \begin{cases} VFC(t), & t \in \mathcal{T}, \\ f_{\mathrm{XGB}}\big(P_{\mathrm{nom}},\, \mathbf{C}(t)\big), & \text{otherwise}. \end{cases}$$

The extracted HI serves as the primary input to the subsequent Transformer-GRU deep learning architecture for RUL prediction, establishing a solid foundation for accurate prognostics under dynamic operating conditions.

Hybrid Transformer-GRU architecture for RUL prediction

To predict the RUL from the extracted HI, we design a hybrid deep learning model that integrates Transformer encoders and Gated Recurrent Units (GRUs). This combination leverages the Transformer's ability to capture long-range dependencies and the GRU's efficiency in modeling temporal dynamics.

The input consists of a normalized multivariate time series:

$$X(t) = [\mathbf{HI}(t), \mathbf{C}(t)]$$

rescaled to $[0, 1]$ using min–max normalization:

$$X'(t) = \frac{X(t) - X_{\min}}{X_{\max} - X_{\min}}.$$

We generate overlapping sliding windows of length L from the normalized series. Each window is first processed by the Transformer module, where each time step is projected into query (Q), key (K), and value (V) vectors. Attention scores are computed as:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}\left(\frac{QK^{\top}}{\sqrt{d_k}}\right) V,$$

where d_k is the dimension of the key vectors. Multi-head attention layers with residual connections and layer normalization capture contextual patterns across time.

The output sequence from the Transformer, x_t^{trans}, is then fed into a GRU layer, which updates its hidden state via:

- Update gate: $u_t = \sigma(W_u \cdot [c_{t-1}, x_t^{\text{trans}}])$
- Reset gate: $r_t = \sigma(W_r \cdot [c_{t-1}, x_t^{\text{trans}}])$
- Candidate state: $\tilde{c}_t = \tanh(W \cdot [r_t \odot c_{t-1}, x_t^{\text{trans}}])$
- Final state: $c_t = (1 - u_t) \odot c_{t-1} + u_t \odot \tilde{c}_t$

This architecture captures both global and local temporal relationships in the degradation signal, enabling accurate and robust RUL predictions under dynamic operating conditions. The key parameters of the Transformer-GRU model, along with their corresponding values, are summarized in Table 3. In our experiments, chronological split is adopted; 80% of the data was used for training, while the remaining 20% was reserved for testing.

Model Evaluation Metrics

To evaluate model performance, we use three standard error metrics (Benaggoune, Yue, Jemei, & Zerhouni, 2022):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - p_i)^2} \tag{5}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|y_i - p_i| \tag{6}$$

$$\mathrm{MAPE} = \frac{100}{N}\sum_{i=1}^{N}\frac{|y_i - p_i|}{|y_i|} \tag{7}$$

where y_i and p_i are the true and predicted values of the HI, and N is the number of test samples.

The next section presents the prediction results and compares the proposed framework with established benchmark methods.

4. RESULTS AND DISCUSSIONS

This section presents the evaluation of the proposed framework using real-world data from three PEMFC stacks embedded in GEH2 systems, each operating under different dynamic conditions. The performance of our method was compared against several well-known models: LSTM (Long Short-Term Memory) (Liu et al., 2019), TCN (Temporal Convolutional Network) (Zhang, Hou, Li, Chen, Wang, Lüddeke, et al., 2025), MSTCN (Multi-Scale Temporal Convolutional Network) (Deng, Bi, Liu, & Yang, 2022), and Transformer (Fu et al., 2024).

Table 4 presents the numerical results and Figure 3 visually compares the performance of these models using RMSE, MAE, and MAPE metrics across all three PEMFCs.

The proposed approach, which combines a learned Health Indicator with a Transformer-GRU architecture, consistently outperformed all benchmark methods across all PEMFC units in terms of RMSE, MAE, and MAPE. Notably, for PEMFC62, our model achieved a substantial reduction in RMSE, over 60% lower than the second-best method, MSTCN. Similar improvements were observed for

Parameter	Description	PEMFC62	PEMFC63	PEMFC52
Epochs	Maximum number of training iterations	100	150	150
Number of heads	Number of attention heads in Transformer	4	12	12
Number of layers	Number of Transformer encoder layers	2	1	1
Model dimension	Dimension of the embedding space	64	64	64
Sequence length	Number of time steps in each input sequence	20	20	20
GRU units	Number of units in the GRU layer	128	128	128
Batch size	Number of samples processed per update	32	32	32
Dropout	Dropout rate for regularization	0.2	0.1	0.1
Patience	Epochs with no improvement before early stopping	10	10	10

Table 3. Transformer-GRU model hyperparameters for each PEMFC.

Method	PEMFC62			PEMFC63			PEMFC52		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
LSTM	0.0524	0.0471	0.23%	0.0870	0.0625	0.31%	0.0700	0.0537	0.46%
TCN	0.0453	0.0421	0.21%	0.0963	0.0814	0.40%	0.1465	0.1317	1.13%
MSTCN	0.0385	0.0359	0.18%	0.0692	0.0576	0.28%	0.0966	0.0829	0.71%
Transformer	0.0579	0.0553	0.27%	0.0958	0.0865	0.42%	0.1044	0.0871	0.75%
Proposed Method	**0.0151**	**0.0098**	**0.05%**	**0.0387**	**0.0312**	**0.15%**	**0.0517**	**0.0435**	**0.37%**

Table 4. Comparison of prediction performance between the proposed method and benchmark models on three PEMFC datasets

PEMFC63, where it reduced RMSE by more than 44%. Even in the more challenging case of PEMFC52, which exhibits highly variable degradations, the proposed method still achieved the best overall performance.

Among the benchmark methods, MSTCN performed well on PEMFC62 and PEMFC63 due to its ability to capture multi-scale temporal patterns, while LSTM was better suited to PEMFC52, where its recurrent nature helped model less structured degradation trends. Standard Transformer models, however, consistently underperformed, suggesting that attention mechanisms alone may be insufficient for modeling PEMFC degradation without additional temporal context.

All models, including the proposed one, show different levels of prediction accuracy across the three PEMFC units, highlighting the variability in their respective degradation behaviors. PEMFC62 yields the lowest prediction errors overall, followed by PEMFC63, whereas PEMFC52 consistently records the highest errors, suggesting it undergoes more irregular or complex degradation. The advantage of the proposed method is most apparent in PEMFC62, where it achieves significantly better accuracy than the other approaches. In contrast, PEMFC52 proves more challenging for all models, as indicated by higher MAPE values, pointing to more unstable and difficult-to-predict degradation patterns in this unit.

In summary, the proposed approach achieved the most accurate and robust predictions across all test cases. Its ability to generalize across different degradation profiles and maintain low error rates under varying operating conditions makes it highly suitable for real-world PEMFC applications. These results highlight the effectiveness of the proposed method in capturing true degradation trends from voltage data, despite the masking effects of dynamic power demand, and demonstrate its practical value for predictive maintenance and fuel cell lifecycle optimization.

5. CONCLUSION

This work tackled the challenge of accurately predicting the Remaining Useful Life (RUL) of PEMFCs operating under the highly dynamic and variable conditions typical of GEH2 electro-hydrogen generators. Traditional HIs derived from raw voltage or power signals often fail to perform reliably in such environments due to their sensitivity to transient load variations.

To address this, we proposed a simple yet effective HI extraction method based on XGBRegressor, capable of isolating degradation-specific trends from voltage data while remaining robust to short-term operational fluctuations. This Health Indicator serves as a stable foundation for long-term prognostics under real-world conditions.

Building on this, we developed a hybrid deep learning model combining Transformer and GRU layers, leveraging both attention mechanisms and recurrent processing to effectively model temporal degradation patterns. The proposed model consistently outperformed state-of-the-art benchmarks across multiple evaluation metrics and PEMFC units, demonstrating strong predictive accuracy and generalization on a diverse industrial dataset.

Overall, the proposed framework offers a robust, inter-

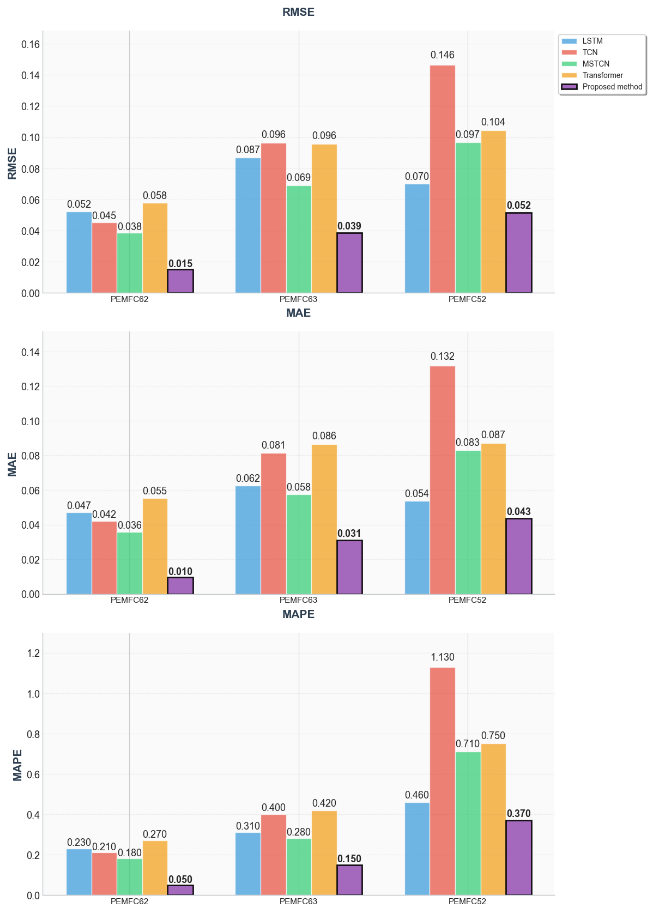

Figure 3. Comparison of RMSE, MAE, and MAPE between the proposed method and benchmark methods across the three PEMFCs.

pretable, and scalable solution for PEMFC RUL prediction in dynamic, real-world settings. Its adaptability to non-stationary conditions and practical relevance to client-driven usage patterns make it well-suited for deployment in industrial hydrogen energy systems.

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