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## ORIGINAL ARTICLE

# Trend-focused dynamic degradation prediction based on echo state networks in automotive fuel cells

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**Abstract**

Fuel cell technology is a promising alternative to traditional internal combustion engines in various applications, especially in transportation applications. However, the high cost and limited lifetime of fuel cells have hindered their widespread commercialization. Accurately predicting fuel cell lifetime is crucial for reducing the cost of ownership, ensuring safety, and promoting the adoption of this technology. The objective of the present work is to develop a tool that is able to estimate the lifespan of a proton exchange membrane fuel cell and to predict its behavior to anticipate failures. Therefore, this paper contributes to proposing a multi-input time-series prediction network based on an echo state network, which takes the future current into consideration. A degradation trend extraction method is proposed in this paper and the remaining useful life of the fuel cell is predicted. Results have shown that the proposed methods in both short-term and long-term prediction have achieved satisfying prediction accuracy.

**KEYWORDS**

automotive, degradation trend extraction, echo state network, performance prediction, proton exchange membrane fuel cell

## 1 | INTRODUCTION

Fuel cell technology is a promising alternative to traditional internal combustion engines in various applications, including transportation and stationary power generation.<sup>1</sup> However, the high cost and limited lifetime of fuel cells have hindered their widespread commercialization.<sup>2</sup> Accurately predicting fuel cell lifetime is crucial for reducing the cost of ownership, ensuring safety, and promoting the adoption of this technology.

The prediction of fuel cell lifetime is a complex and multidisciplinary research topic as the lifetime of fuel cells is affected by multiple factors, such as material degradation,

electrochemical reactions, water management, and operating conditions. These factors interact with each other and vary with time, making it challenging to accurately model and predict fuel cell lifetime. Among them, on-board dynamic operating conditions are a key trigger for the accelerated degradation of automotive fuel cell performance.<sup>3</sup> Complex road conditions such as urban, suburban, and highway conditions and variable environmental conditions such as varying temperature and humidity tend to cause dynamic changes in the operating characteristics and frequent fluctuations in fuel supply, pressure, temperature, and humidity of the automotive fuel cell system, resulting in accelerated degradation and reduced lifetime of

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key fuel cell components. The process and mechanism of fuel cell degradation are complex.<sup>4</sup> Dynamic load and frequent start-stop lead to alternating potential and fluctuations in gas supply response inside the fuel cell, resulting in flooding, lack of air, and local overheating, causing corrosion of electrode materials and shortening the service life of the fuel cell.<sup>5</sup> The evolution of environmental physical parameters such as temperature and relative humidity causes fluctuations in cathode air pressure and oxygen content, leading to electrochemical degradation of the electrodes and membrane. Besides, the increase in interlayer contact resistance due to fluctuations in mechanical stress will also further accelerate the degradation of the membrane electrode assembly, exacerbating the degradation of the fuel cell performance and seriously affecting the reliable operation of automotive fuel cell systems.

The multi-influence coupling and interaction mechanisms between the input and output characteristics of the system make the fuel cell performance degradation strongly nonlinear, and the compact assembly of the stack makes its internal parameters difficult to measure. In addition, as the changes in operating parameters under the dynamic conditions of the automotive fuel cell can hardly be predicted, this makes it difficult to accurately predict the lifetime of automotive fuel cells without a comprehensive degradation information structure, which makes it more difficult to optimize the lifetime control, and is not conducive to the positive design of automotive fuel cell systems. As automotive fuel cells are expensive to maintain and replace, the accuracy and reliability of life prediction methods are crucial to reduce costs and improve efficiency.

Several techniques have been proposed and developed for predicting fuel cell lifetime, including empirical models, mathematical models, and data-driven models. Empirical models rely on experimental data to establish relationships between fuel cell performance and lifetime, while mathematical models use fundamental principles and mathematical equations to describe the physical and chemical processes in fuel cells. Bressel et al. proposed to use an extended Kalman filter to estimate the state of a single linear performance degradation parameter based on the assumption of linearity in the ohmic resistance and ultimate current density of the fuel cell, to calculate the remaining service life.<sup>6</sup> Similarly, Jouin et al. used a particle filter algorithm to perform state estimation of multiple performance degradation parameters in a semi-empirical performance degradation model for fuel cells, using the fuel cell output voltage as an observation, to achieve fuel cell performance degradation prediction based on a semiempirical model.<sup>7</sup> Data-driven models leverage machine learning and artificial intelligence algorithms to extract patterns and relationships from

large datasets. This type of prediction method uses historical data to train relevant behavioral models with good nonlinear fitting capability, and has good results in dealing with nonlinear and coupled performance degradation characteristics of fuel cells. Commonly used data-driven prediction methods include recurrent neural networks (RNNs),<sup>8</sup> echo state networks (ESNs),<sup>9</sup> and long short-term memory.<sup>10</sup> Researchers have continued to make improvements in terms of accuracy and model adaptability on data-driven prediction methods, such as using self-selection of key parameters in neural networks through hyperparameter tuning methods based on evolutionary algorithms<sup>11</sup> and the use of neural networks combined with traditional time-series forecasting models to weaken the error accumulation problem of forecasting models.<sup>12</sup> However, most of the methods used in the above research work are suitable for predicting steady-state systems, and the prediction results are better when the input variables are single and remain constant; however, in real-world automotive fuel cell systems, the output characteristics of fuel cells are characterized by high nonlinearity due to dynamic changes in operating conditions. Therefore, the development of online prediction methods that can describe the dynamic performance degradation mechanisms of fuel cells is particularly critical and is a much needed research effort with great research value.

To address the above issues, the current research has explored two main aspects: first, the steady-state representation of the dynamic output characteristics of fuel cells is investigated, and then the prediction method of the steady-state performance degradation index is used for prediction. For example, Hua et al. proposed a fuel cell performance degradation prediction method based on the relative power loss rate.<sup>13</sup> Li et al. fitted the voltage signal by segmenting the linear parameter variation equivalent model and constructed a virtual steady-state voltage for life prediction based on the model identification method.<sup>14</sup> Wang et al. used an adaptive Brownian bridge aggregation method to extract the performance indicators from the fuel cell equivalent circuit model that can represent the degradation evolution.<sup>15</sup> He et al. used an unsupervised learning-based autoencoder to encode the load cycles and extracted the intermediate layer features as degradation indicators for prediction, which better restored the degradation process of fuel cells under dynamic loads.<sup>16</sup> However, such methods are still essentially predictions of the steady-state characteristics of the fuel cell and lack the consideration of information on the dynamic operating conditions in the actual operation of the fuel cell. Another solution is to make predictions by coupling the known operating conditions, that is, current intensity, temperature, pressure, and so forth. They are used as inputs to the

prediction model, so that the dynamic changes in the fuel cell output characteristics can be predicted. For example, Jin et al. found that hydrogen inlet and outlet pressures can reflect the performance degradation characteristics of fuel cells through sensitivity analysis of multidimensional data, and using them as inputs to a neural network can improve the fuel cell life prediction results.<sup>17</sup> Xie et al. used deep neural networks to predict system parameters such as fuel cell current and air temperature, and proposed a method to reconstruct voltage profiles through system parameters.<sup>18</sup> Liu et al. classified the automotive operating conditions of fuel cells into four categories based on current density, and trained a multi-input fuel cell performance degradation prediction model based on Bayesian ridge regression and Gaussian process regression using the operating times of the four categories as inputs.<sup>19</sup>

ESNs are a specialized form of RNNs that are particularly well-suited for temporal or time-series data prediction tasks. Unlike traditional RNNs, ESNs do not require backpropagation through time for training the hidden layer weights. Only the output weights are trained, which significantly reduces the computational cost and complexity. They also have a high memory capacity due to their dynamic reservoir, which can capture long-term dependencies within the data more effectively than many other types of networks. Particularly pertinent to our work, Morando et al. have first discovered the possibility of using ESN in proton exchange membrane fuel cell (PEMFC) lifetime prediction<sup>9</sup> and applied it to predict the degradation of the fuel cell under constant load. Hua et al. have explored the use of ESNs in forecasting the degradation of the fuel cell by combining wavelet transform method.<sup>20</sup> Their findings corroborated the potential of ESNs to capture the nuanced degradation behaviors inherent to fuel cells, which indicated that ESNs not only provided comparable accuracy but also required significantly less computational resources, underscoring their suitability for real-time applications. The objective of the present work is to develop a tool that is able to estimate the lifespan of a PEMFC and to predict its behavior to anticipate failures. Therefore, to dynamically predict the degradation performance of automotive fuel cell under variable operation conditions, this paper contributes to proposing a multi-input time-series prediction network based on a multi-input ESN, which takes the future current into consideration. Nevertheless, in real-case applications, the future load profile is not available. The aim of this paper is not only to develop an accurate prognostic tool but also to propose a solution to predict the lifetime of the PEMFC, which is achieved by extracting the degradation trend.

The following of this paper will first introduce the experimental data used to train and to validate the proposed ESN-based fuel cell performance prediction method. Then, the methodology of this paper is explained and the results are demonstrated and discussed before concluding.

## 2 | DATA DESCRIPTION

The fuel cell stacks utilized in the experiments were fabricated by company PRAGMA Industries with an open cathode and dead-end anode structure. To evaluate their degradation for transport applications, a long-term test was initiated in FCLAB Research Federation.<sup>14</sup> Table 1 provides some of the operation condition parameters used during the evaluations and Figure 1A showcases the experimental platform where two stacks were simultaneously tested, with the only shared resource being the common hydrogen supply, which is fixed near to 0.35 bar. The current load is controlled by a programmable electronic direct current load, which simulates the load profile derived from a fuel cell used as a range extender in a battery-powered light mobile bike. The fuel cell activates when the state-of-charge of the bike's battery falls below a predefined threshold. When the fuel cell is enabled, the current increases gradually from 0 to 8 A. The average power of the hydrogen bike is 53.6 W, as shown in Figure 1B. This paper focuses on studying one of the stacks that ran for 1750 h with the obtained current profile. The stack temperature is managed by adjusting the air fan's speed, which is regulated by altering the duty cycle of a 25-kHz pulse width modulation signal. Optimal operating temperatures at various current levels are referenced for guidance. A classic proportional-integral-derivative controller is employed

TABLE 1 Fuel cell stack parameters.

Parameter	Value
Number of cells	15
Active surface (cm <sup>2</sup> )	33.625
Temperature (°C)	25–72
Current density (A/cm <sup>2</sup> )	0–0.238
Anodic relative humidity	0
Cathodic relative humidity (%)	45–55
Maximum allowable pressure difference between anode and cathode (bar)	0.35
Pressure at air inlet	atm
Pressure at hydrogen inlet (bar)	1.35

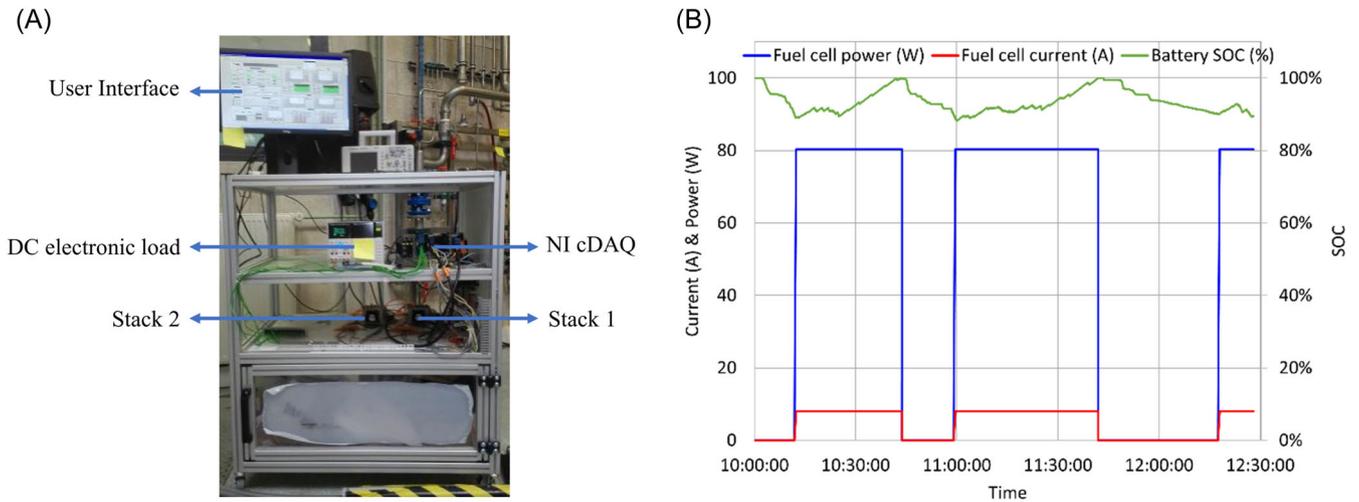


FIGURE 1 (A) Fuel cell degradation experiment platform and (B) fuel cell degradation experiment profile and power battery SOC variation. cDAQ, compact data-acquisition; DC, direct current; NI, National Instruments; SOC, state-of-charge.

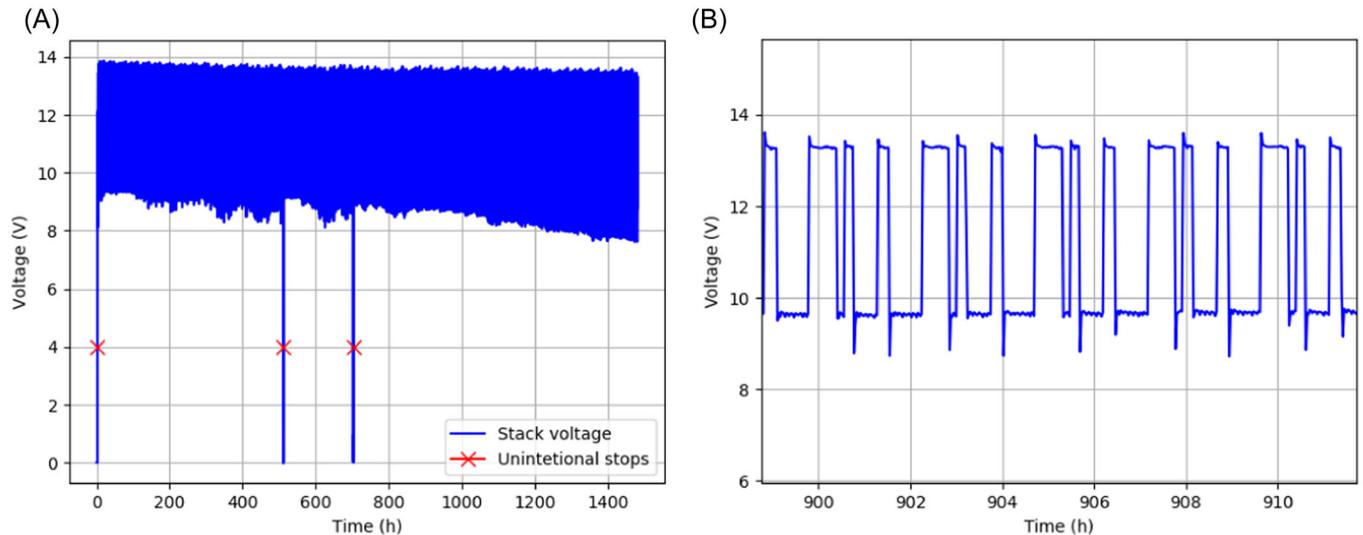


FIGURE 2 (A) Measured fuel cell voltage and (B) details of measured fuel cell voltage.

to achieve precise temperature control. Additionally, the fuel cells are self-humidifying, eliminating the need for an external humidifier on the cathode side. The voltage measurements are displayed in Figure 2.

### 3 | METHODOLOGY

#### 3.1 | Echo state network

ESN is a type of RNN that is often used for time-series prediction and other dynamic system modeling tasks. At each time step, the network takes an input vector  $x(t)$  and

generates an output vector  $y(t)$ , which depends on the current state of the network. The output weight matrix is typically learned by solving a linear regression problem using a training set of input-output pairs. The key idea behind ESNs is that the recurrent weight matrix is randomly initialized and only the output weight matrix is learned. This allows the network to capture complex temporal dynamics without suffering from the vanishing gradient problem that often occurs in traditional RNNs. In addition, ESNs are relatively easy to train and require less computational resources compared to other RNN architectures. The state update model of ESN is written as

$$\tilde{u}(t) = f(w_{res}u(t-1) + w_{in}x(t)), \quad (1)$$

$$y(t) = g(w_{out}u(t)), \quad (2)$$

where  $x(t)$  and  $y(t)$  are the input and output,  $u(t)$  is the internal state in the reservoir, and  $\tilde{u}(t)$  is its update,  $\tilde{u}(t) = u(t) - u(t-1)$ ,  $w_{in}$  is the input weight matrix,  $w_{res}$  is the recurrent weight matrix in the reservoir, and  $w_{out}$  is the output weight matrix. The  $\tanh$  function is generally adopted as the activation function  $f(\cdot)$  of the reservoir, and  $g(\cdot)$  of the output layer could be defined with a simple linear function, such as  $g(\cdot) = 1$ .  $w_{in}$  and  $w_{res}$  are initialized randomly and they are constant so that there is no need to train them. Only  $w_{out}$  is going to be trained by linear regression. The structure of ESN is shown in Algorithm 1.

#### Algorithm 1. Procedure of implementing echo state network

1. Define the echo state network structure and parameters
  - Initialize  $w_{in}$  randomly
  - Initialize  $w_{res}$  with sparse connectivity and set spectral radius value
  - Initialize  $w_{out}$  to zero or small random values
2. Set hyperparameters
  - Set reservoir size, input size, output size, leaking rate, and so forth
3. Reservoir state initialization: Initialize  $u(t)$  to zero
4. Data preparation: Normalize and split the time series into training and testing sets
5. Training phase:
  - for each training input in training set do
    - Update  $u(t)$  with  $w_{in}$ ,  $w_{res}$ , and leaking rate
    - Collect states and desired outputs in matrices for training
  - end for
  - $w_{out}$  = Train using linear regression on collected states
6. Testing phase:
  - for each test input in testing set do
    - Update  $u(t)$  with  $w_{in}$ ,  $w_{res}$ , and leaking rate
    - Compute forecast using the trained  $w_{out}$  and current  $u(t)$
    - Store forecast for evaluation
  - end for
7. Evaluate the model performance with evaluation metrics

When working with prediction problems, it is common to choose both a training window and a prediction window. The training window determines the length of the input sequence, while the prediction window signifies how many steps will be predicted. In

applications such as fuel cell prognostics, the training window length is determined based on the amount of available input data. When conducting short-term prediction, specifically, if there are  $N$  available measurements, a window length of  $p$  is used for the input sequence, expressed as

$$\mathbf{x}(i) = [s(i+1), s(i+2), \dots, s(i+p)], \quad (3)$$

$$i = 0, \dots, N-p.$$

Then, the corresponding output with a prediction window length of  $q$  is written as

$$\mathbf{y}(i) = [\hat{s}(i+p+1), \hat{s}(i+p+2), \dots, \hat{s}(i+p+q)], \quad i = 0, \dots, N-p. \quad (4)$$

In this paper, the inputs are the current signal at time  $t$  and the voltage signal at time  $t-1$ , while the output is the voltage signal at time  $t$ .

### 3.2 | Degradation trend extraction

Multiplicative decomposition is a statistical method used for time-series analysis to decompose a time series into several components. The idea behind the decomposition is to isolate the trend, cyclical, and seasonal components of the time series. In multiplicative decomposition, the original time series is represented as the product of these three components:

- *Trend component*: represents the long-term increasing or decreasing behavior of the time series.
- *Cyclical component*: represents periodic fluctuations in the time series that are not of fixed frequency, such as business cycles or economic cycles.
- *Seasonal component*: represents the regular pattern of fluctuations that occur within a fixed time period.

The mathematical formula for multiplicative decomposition can be written as  $Y(t) = T(t)*C(t)*S(t)$ , where  $Y(t)$  is the observed value of the time series at time  $t$ ,  $T(t)$  is the estimated trend component,  $C(t)$  is the estimated cyclical component, and  $S(t)$  is the estimated seasonal component. The pseudocode of implementing the multiplicative decomposition is shown in Algorithm 2. Multiplicative decomposition is useful for identifying patterns and trends in time-series data, which can be helpful in forecasting and decision-making.

### Algorithm 2. Procedure of implementing multiplicative decomposition

Data preparation

Input: Time-series data ( $Y(t)$ ), where  $t = 1, 2, \dots, n$

Step 1: Initialize

- Set seasonal length ( $L$ ) based on periodicity of data
- Divide  $Y(t)$  into segments of length  $L$

Step 2: Seasonal component estimation

- Calculate the average of each segment to get initial seasonal component ( $S(t)$ )
- Normalize  $S(t)$  such that the product of seasonal components over one period equals 1

Step 3: Trend and cyclical component estimation

- Detrend the time series by dividing  $Y(t)$  by  $S(t)$  to obtain detrended series ( $D(t)$ )
- Apply a moving average on  $D(t)$  to extract the trend component ( $T(t)$ )
- Calculate the cyclical component ( $C(t)$ ) by dividing  $D(t)$  by  $T(t)$

Step 4: Multiplicative decomposition

- Express the original time series as the product of the components:  $Y(t) = T(t) * C(t) * S(t)$

Step 5: Output

- Return the trend component ( $T(t)$ ), seasonal component ( $S(t)$ ), and cyclical component ( $C(t)$ )

End

As the fuel cell is operated under dynamic conditions in automotive applications, the trend, rather than the magnitude of the stack voltage, is the key element to determine the degradation of the fuel cell. As the magnitude of the time series may change due to ageing phenomenon, multiplicative decomposition is used to decompose the signal into trend, seasonal values, and residual values, as shown in Figure 3.

In the decomposition results, the trend refers to the increasing or decreasing value in the series, the seasonal values refer to the repeating short-term cycles in the series and the residual values refer to the random variation in the series, which in our case, are the noise in the voltage measurement. Therefore, to indicate the degradation of the stack, the trend of the decomposition is extracted as the degradation feature and will be used to train the prognostics network to predict the fuel cell degradation, shown in Figure 4.

### 3.3 | PEMFC performance prediction

In this study, both short-term and long-term performance predictions for fuel cells using the proposed prediction methodologies are explored. Short-term prediction is characterized by its immediacy; it forecasts

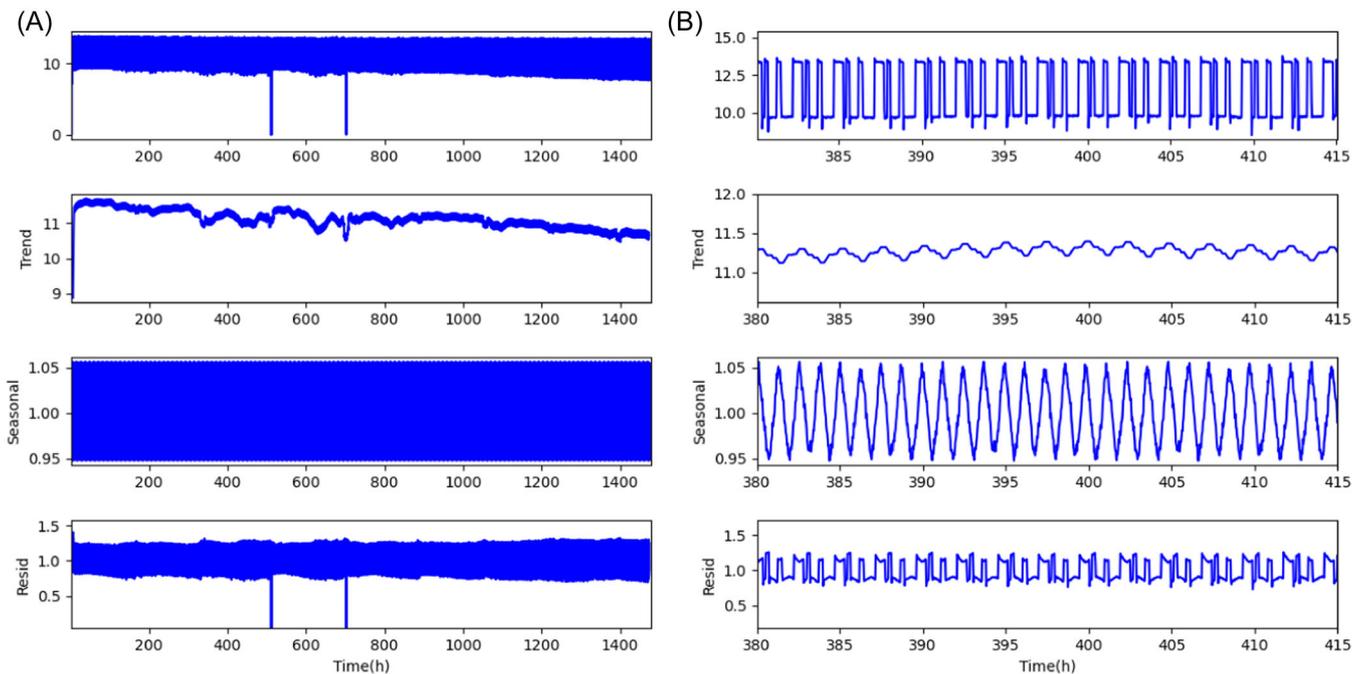


FIGURE 3 (A) Multiplicative decomposition result and (B) details of decomposition result.

only a few time steps ahead based on recent historical data. After each prediction, actual measurements are incorporated to update the model, thereby refining subsequent short-range predictions. Figure 5A shows a one-step-ahead prediction procedure. These short-term predictions facilitate dynamic adjustments in system control and management strategies in response to anticipated conditions.

In the long run, one may need to master the long-term performance degradation of fuel cells because it allows for proactive maintenance and replacement planning. Fuel cell systems rely on a combination of materials and chemical processes to convert fuel into electricity, and as these components degrade over time, their performance declines. If left unchecked, this degradation can lead to reduced efficiency, increased downtime, and even complete failure of the fuel cell system. Therefore, long-term predictions operate independently of real-time measurements during the prediction phase. Once initiated, this approach relies solely on predicted values for future forecasting, thereby generating a sequence that projects the fuel cell stack's end-of-life (EOL). Long-term predictions provide strategic insights, such as estimating the remaining useful life (RUL), which are critical for maintenance scheduling, operational optimi-

zation, and minimizing unexpected failures.<sup>21</sup> It is worth noting that long-term prediction poses greater challenges than its short-term counterpart due to the inherent uncertainty of extended temporal horizons. An effective prediction method must therefore be adept at navigating both the immediate and distant futures to accurately capture the behavior of the fuel cell under varying conditions. To realize long-term prediction purposes, the standard approach of performing one-step-ahead prediction is modified, as shown in Figure 5B. This modification allows for multistep prediction. The input sequence used for prediction consists of a length of  $l$  and data collected until the end. The model outputs a single predicted value, but to continue making predictions, the predicted value from the previous step is added back to the input sequence. This process continues until the completion of the test phase.

## 4 | RESULTS AND DISCUSSION

### 4.1 | Short-term performance prediction

In the experiment, 53,279 points of ageing data are collected for prediction method validation. In all, 30,000 points are used for training and the rest for testing. The

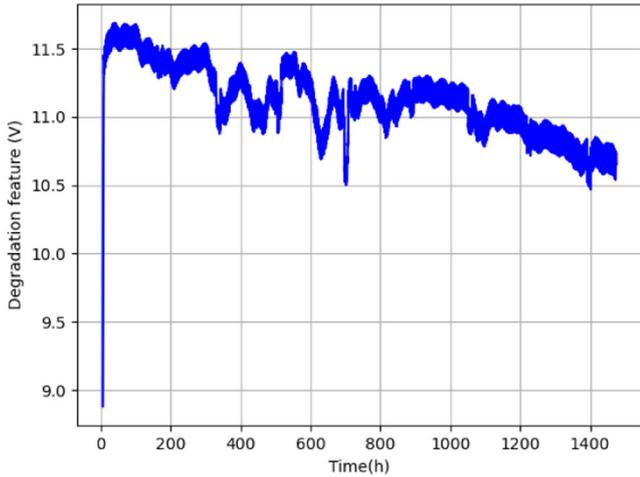


FIGURE 4 Degradation feature extraction result.

TABLE 2 Configuration of the proposed multistep echo state network.

Parameter	Value
Input parameter	2
Output parameter	1
Input window length	20
Output window length	1
Number of neurons	2000
Leaking rate	0.5
Spectral radius	0.5
Regression parameter	$10^2$

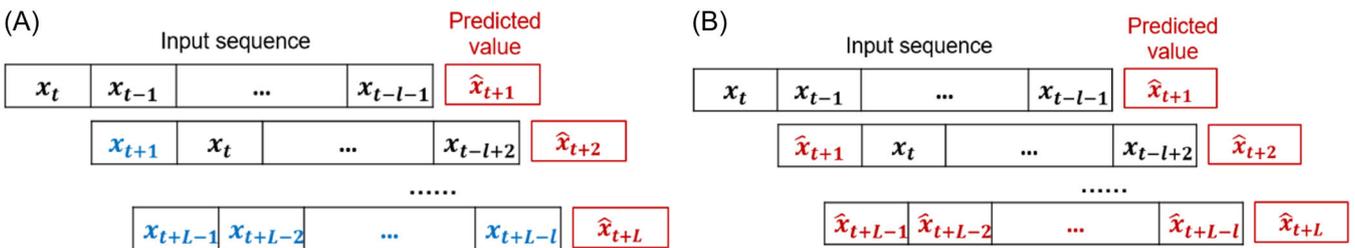


FIGURE 5 Procedure of short-term and long-term prediction. (A) Short-term performance prediction and (B) long-term performance prediction.

configuration of the proposed multistate ESN is specified in Table 2. The ESN was implemented in a Python environment, leveraging *easyn* package. For the setup, we utilized the 12th Gen Intel Core i7-12700H 2.30 GHz. The training of the network was conducted using backpropagation through time. The training phase takes an average 3 s.

The training and testing results are shown in Figure 6 and details in Figure 7. As it can be seen from the results that the fuel cell degrades along with the experiment time and the voltage changes dynamically due to the current load. By adding a current signal as one of the inputs, the proposed prediction method can predict the fuel cell performance accurately during its whole life

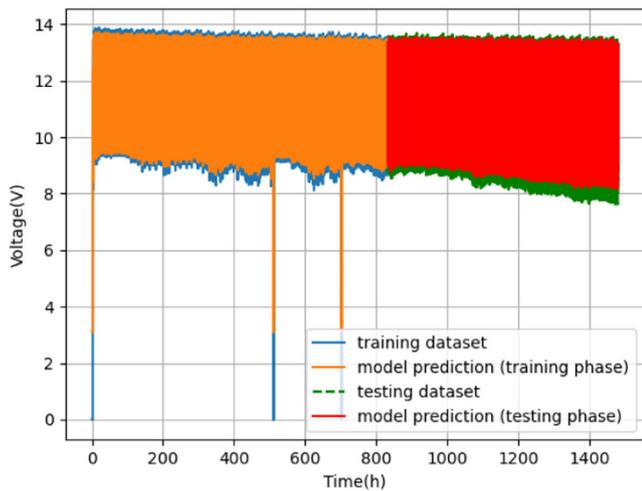


FIGURE 6 Short-term prediction results of training phase and testing phase.

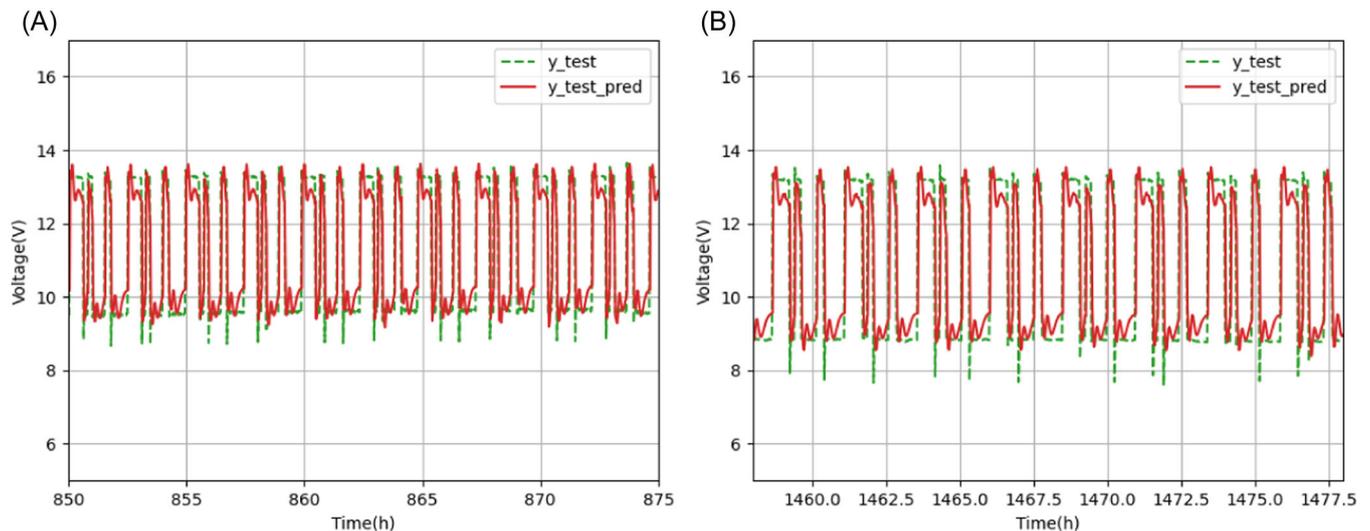


FIGURE 7 Zoom results at the beginning and the end of the testing phase. (A) Zoom results at the beginning of the testing phase and (B) zoom results at the end of the testing phase.

cycle. However, the prediction results are less satisfying during the end period of the testing phase than those during the beginning period. This may be due to the accumulating degradation effects and can be improved by increasing the prediction window length.

## 4.2 | Long-term degradation prediction

Further analysis of the proposed method for predicting fuel cell degradation is presented in Figure 8, with a split ratio between training and testing phases remaining constant. The sampled and smoothed data are utilized to conduct long-term predictions, showing that the multi-input ESN-based model successfully predicts the degradation trend of the fuel cell without requiring any measurements during the testing phase. This conclusion is supported by the comparison between the red dotted line and the green line on the graph. The root-mean-square error of the predicted results during the testing phase is lower than 0.06, indicating high prediction accuracy. These findings suggest the feasibility of further implementing the proposed method for predicting fuel cell degradation in real-world applications.

The analysis of the RUL estimation for the fuel cell, evaluated by Equation (5), is depicted in Figure 9. The figure illustrates a comparison between the predicted RUL and the true RUL, where  $t_{EOL}$  represents the EOL failure threshold, and  $t_\lambda$  denotes the current time. The prediction tests were initiated at four different starting points, that is, [750; 800; 850; 900] hour, resulting in corresponding predicted RULs of [444; 425; 343; 316]. The predicted RUL errors were computed relative to the

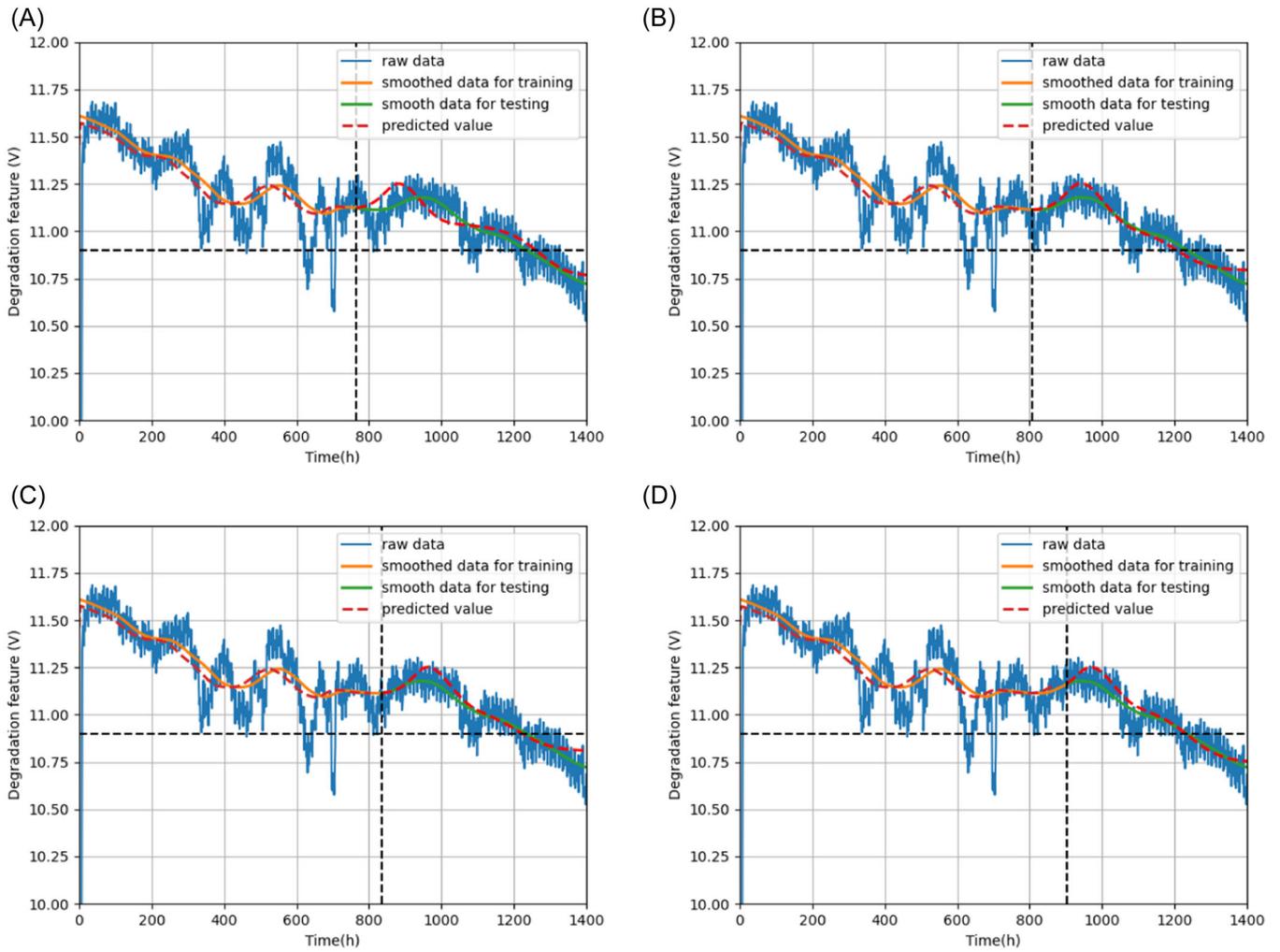


FIGURE 8 Long-term prediction results. Prediction starting at (A) the 750th hour, (B) the 800th hour, (C) the 850th hour, and (D) the 900th hour.

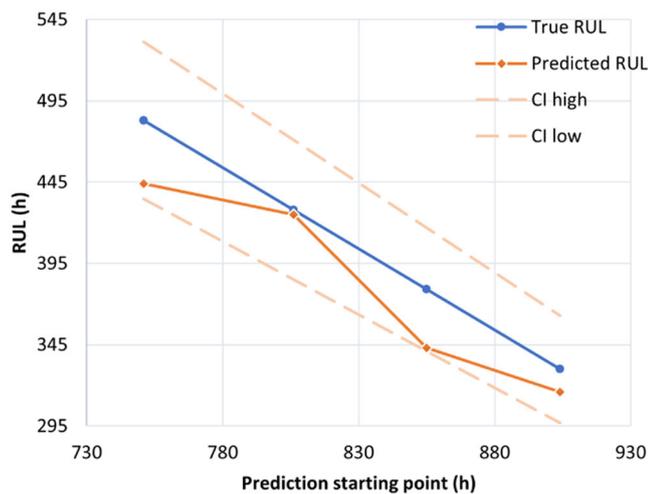


FIGURE 9 RUL comparison results. CI, confidence interval; RUL, remaining useful life.

true RUL, yielding [39; 3; 36; 14] within a 10% confidence interval. Interestingly, all the predictions were early predictions, which meet the requirements for predictive maintenance. These results demonstrate the effectiveness and accuracy of the proposed approach for predicting the RUL of fuel cells.

$$\hat{RUL} = \hat{t}_{EOL} - t_{\lambda}. \quad (5)$$

## 5 | CONCLUSION

In conclusion, this paper proposed an ESN-based fuel cell performance prediction method for both short-term performance prediction and long-term degradation prediction in automotive applications. The proposed

multi-input time-series prediction network based on ESN, which takes future current into consideration, is a promising method to estimate fuel cell lifespan and predict potential failures. Additionally, the proposed degradation trend extraction method addresses the issue of unavailable future load profiles, providing a reliable means for predicting the RUL of the fuel cell. The prediction results show that the proposed prediction method has reached satisfying accuracy and is suitable for dynamic load applications.

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## REFERENCES

- Cullen DA, Neyerlin KC, Ahluwalia RK, et al. New roads and challenges for fuel cells in heavy-duty transportation. *Nat Energy*. 2021;6(5):462-474. doi:10.1038/s41560-021-00775-z
- Yue M, Lambert H, Pahon E, Roche R, Jemei S, Hissel D. Hydrogen energy systems: a critical review of technologies, applications, trends and challenges. *Renewable Sustainable Energy Rev*. 2021;146:111180.
- Lin R, Li B, Hou YP, Ma JM. Investigation of dynamic driving cycle effect on performance degradation and micro-structure change of PEM fuel cell. *Int J Hydrogen Energy*. 2009;34(5):2369-2376. doi:10.1016/j.ijhydene.2008.10.054
- Ren P, Pei P, Li Y, Wu Z, Chen D, Huang S. Degradation mechanisms of proton exchange membrane fuel cell under typical automotive operating conditions. *Prog Energy Combust Sci*. 2020;80:100859. doi:10.1016/j.peccs.2020.100859
- Zhang T, Wang P, Chen H, Pei P. A review of automotive proton exchange membrane fuel cell degradation under start-stop operating condition. *Appl Energy*. 2018;223:249-262. doi:10.1016/j.apenergy.2018.04.049
- Bressel M, Hilairat M, Hissel D, Ould Bouamama B. Extended Kalman filter for prognostic of proton exchange membrane fuel cell. *Appl Energy*. 2016;164:220-227. doi:10.1016/j.apenergy.2015.11.071
- Jouin M, Gouriveau R, Hissel D, Péra MC, Zerhouni N. Prognostics of PEM fuel cell in a particle filtering framework. *Int J Hydrogen Energy*. 2014;39(1):481-494. doi:10.1016/j.ijhydene.2013.10.054
- Zhou D, Al-Durra A, Zhang K, Ravey A, Gao F. Online remaining useful lifetime prediction of proton exchange membrane fuel cells using a novel robust methodology. *J Power Sources*. 2018;399:314-328. doi:10.1016/j.jpowsour.2018.06.098
- Morando S, Jemei S, Hissel D, Gouriveau R, Zerhouni N. Proton exchange membrane fuel cell ageing forecasting algorithm based on echo state network. *Int J Hydrogen Energy*. 2017;42(2):1472-1480. doi:10.1016/j.ijhydene.2016.05.286
- Ma R, Yang T, Breaz E, Li Z, Briois P, Gao F. Data-driven proton exchange membrane fuel cell degradation prediction through deep learning method. *Appl Energy*. 2018;231:102-115. doi:10.1016/j.apenergy.2018.09.111
- Zhang Z, Wang YX, He H, Sun F. A short- and long-term prognostic associating with remaining useful life estimation for proton exchange membrane fuel cell. *Appl Energy*. 2021;304:117841. doi:10.1016/j.apenergy.2021.117841
- Wang C, Li Z, Outbib R, Dou M, Zhao D. A novel long short-term memory networks-based data-driven prognostic strategy for proton exchange membrane fuel cells. *Int J Hydrogen Energy*. 2022;47(18):10395-10408. doi:10.1016/j.ijhydene.2022.01.121
- Hua Z, Zheng Z, Pahon E, Péra MC, Gao F. Remaining useful life prediction of PEMFC systems under dynamic operating conditions. *Energy Convers Manage*. 2021;231:113825. doi:10.1016/j.enconman.2021.113825
- Li Z, Zheng Z, Outbib R. Adaptive prognostic of fuel cells by implementing ensemble echo state networks in time-varying model space. *IEEE Trans Ind Electron*. 2020;67(1):379-389. doi:10.1109/TIE.2019.2893827
- Wang C, Li Z, Outbib R, Dou M, Zhao D. Symbolic deep learning based prognostics for dynamic operating proton exchange membrane fuel cells. *Appl Energy*. 2022;305:117918. doi:10.1016/j.apenergy.2021.117918
- He K, Mao L, Yu J, Huang W, He Q, Jackson L. Long-term performance prediction of PEMFC based on LASSO-ESN. *IEEE Trans Instrum Meas*. 2021;70:1-11. doi:10.1109/TIM.2021.3058365
- Jin J, Chen Y, Xie C, Wu F. Remaining useful life prediction of PEMFC based on the multi-input cycle reservoir with jump network. *Int J Hydrogen Energy*. 2023;48(34):12844-12860. doi:10.1016/j.ijhydene.2022.12.170
- Xie R, Li C, Ma R, Xu L, Zhou X. An explainable data-driven framework for fuel cell aging prediction under dynamic condition. *IEEE Trans Ind Electron*. 2022;70(6):5960-5970. doi:10.1109/tie.2022.3199935
- Liu M, Wu D, Yin C, Gao Y, Li K, Tang H. Prediction of voltage degradation trend for a proton exchange membrane fuel cell city bus on roads. *J Power Sources*. 2021;512:230435. doi:10.1016/j.jpowsour.2021.230435
- Hua Z, Zheng Z, Pahon E, Péra MC, Gao F. Lifespan prediction for proton exchange membrane fuel cells based on wavelet transform and echo state network. *IEEE Trans Transp Electr*. 2022;8(1):420-431. doi:10.1109/TTE.2021.3121179
- Benagoune K, Yue M, Jemei S, Zerhouni N. A data-driven method for multi-step-ahead prediction and long-term prognostics of proton exchange membrane fuel cell. *Appl Energy*. 2022;313:118835. doi:10.1016/j.apenergy.2022.118835

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