

Highlights

A dynamic electrochemical impedance spectroscopy extraction method for PEM water electrolyzers considering time resolution

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- Benchmarking reveals limitations of 5 EIS extraction methods in dynamic states.
- Hybrid method achieves >96% accuracy for real-time dynamic EIS of PEMWE.
- Real PV profiles validate the method's efficiency for fluctuating energy inputs.

A dynamic electrochemical impedance spectroscopy extraction method for PEM water electrolyzers considering time resolution

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Abstract

Electrochemical impedance spectroscopy (EIS) is an efficient in-operando characterization tool for analyzing the internal processes of proton exchange membrane water electrolyzers (PEMWE). However, conventional EIS requires the system to operate under steady-state conditions, which limits its applicability in real-world systems. Dynamic EIS (DEIS) provides a potential approach to capture the variation of internal physical states caused by changes in operating conditions over time. However, existing impedance extraction methods generally rely on a single technique, such as fast Fourier transform and wavelet transform, thereby limiting their capability to analyze nonstationary signals over the full frequency range—from *m*Hz to *k*Hz—in PEMWE systems. To address these limitations, this paper proposes a hybrid method that combines the advantages of several existing time–frequency and instantaneous feature extraction techniques to accurately obtain DEIS under dynamic conditions. This study segments the perturbation signals based on operating variations and applies adaptive processing to ensure accurate impedance extraction during rapid power transitions typical of solar-coupled systems. Simulation and experimental verification under different input power profiles to a PEMWE are conducted in this work. The results demonstrate that the proposed hybrid method achieves a DEIS accuracy exceeding 96%, verifying its effectiveness for PEMWE applications and potential for other electrochemical devices and providing a robust pathway for real-time health monitoring in large-scale hydrogen energy systems.

Keywords: Dynamic EIS, time-resolution, frequency range, proton exchange membrane water electrolyzers, hybrid calculation method

1. Introduction

In recent years, the accelerating pace of climate change and the continuous growth in global energy demand have intensified the need for sustainable and low-carbon energy solutions. Renewable energy sources (RESs), such as solar, wind, hydro, and biomass, have emerged as promising alternatives to conventional fossil fuels due to their environmental benefits and inexhaustible nature. However, the RESs are inherently intermittent and strongly influenced by environmental factors [1]. To ensure continuous and reliable power delivery and improve the stability of the renewable-based energy systems, an intermediate energy storage medium is necessary. Water electrolysis provides a clean pathway to convert the RESs into hydrogen without generating additional pollutants.

Proton exchange membrane water electrolyzers (PEMWEs) have attracted extensive attention due to the high purity of generated hydrogen, rapid dynamic response, compact structure, and ability to operate at large current density range, making them more suitable for operation when coupled with RESs [2]. However, during operation, the power fluctuation of the RESs may lead to accelerated degradation. Additionally, other faults, such as short circuits or membrane damage in PEMWEs, can lead to operational failures and pose potential safety risks [3]. An effective diagnostic tool is expected to improve the operating safety and further extend the lifespan of PEMWEs.

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Electrochemical impedance spectroscopy (EIS) is an efficient in-operando characterization tool for diagnosing the operating status of PEMWEs, as it provides abundant information linked to the internal processes, such as electrode kinetics, mass transport behavior, etc., without interrupting the system's normal operation.

When coupled with data analysis methods like distribution of relaxation times (DRT) and equivalent circuit modeling [4], detailed information regarding internal relaxation processes can be extracted from EIS [5]. Furthermore, by leveraging intelligent algorithms such as machine learning and deep stacked autoencoder, faults occurring under complex operating conditions can be accurately identified and localized [6, 7]. Finally, by integrating EIS functionality directly into the power converter, real-time online measurement and monitoring can be achieved [8], offering a pathway toward autonomous system health management. However, the classical EIS is limited by its foundational assumptions of stationarity, which are impossible to ensure in the real RESs system. To address this implementation gap, an impedance study of non-stationary systems was conducted for the first time in [9], and corresponding measurements were described in [10]. This work, therefore, provided an approach to characterize the PEMWEs under dynamic operations. This technique is known as dynamic electrochemical impedance spectroscopy (DEIS). It is specifically developed to measure system impedance under variable operating conditions, enabling the capture and visualization of the physical, chemical, and electrochemical dynamics within the system [11]. Accurate extraction of DEIS is essential for ensuring that the information being reflected is both precise and reliable.

For classical EIS calculations, the commonly used approach relies on the fast Fourier transform (FFT) to analyze the perturbation and response signals over the entire measurement period [12]. However, conventional EIS methods require the system to remain at steady state for each frequency perturbation. If this condition is not met, significant errors can occur, because the fast Fourier transform (FFT) only captures the average amplitude and phase over the measurement period, failing to resolve transient deviations. To obtain the accurate impedance information under dynamic conditions, several researchers have attempted to shorten the measurement time to ensure an approximate steady state during EIS implementation. In [13], a perturbation method that combines a sinusoidal sweep with two additional signals using different sampling functions enables rapid DEIS extraction; however, its validation under dynamic operating conditions has not yet been demonstrated. By leveraging simultaneous multi-frequency excitation [14], pseudo-random perturbation signals significantly compress the measurement duration. When integrated with a sliding-window algorithm, this approach effectively suppresses impedance estimation artifacts induced by transient operating conditions [15]. Nevertheless, the sliding window must cover at least one period of the lowest-frequency perturbation signal, and the data within each window are assumed to be in a steady state. These requirements can lead to substantial errors for systems requiring low-frequency measurements such as PEMWEs, because one window may span several minutes [16], making it difficult to ensure signal stability within the window. Therefore, this type of method has a limited applicable frequency range and is not suitable for estimating signals containing low-frequency components.

Another category of methods relies on improving the time resolution to extract DEIS information. One approach to address this is to calculate time-resolved EIS using the short-time Fourier transform (STFT) [17], which overcomes the need for the system to remain steady-state during measurement. However, the results are highly sensitive to the stationarity of the signal in one window. In comparison, the wavelet transform (WT) offers better time–frequency resolution under non-stationary conditions due to its translatable and scalable analysis window [18]. Although WT is employed in [19, 20] to extract EIS during the battery charging or discharging process, the temporal information that WT is capable of providing is not fully utilized. The battery impedance is still treated as being measured at a quasi-steady-state operating point, and the results are primarily compared with those obtained from commercial instruments. In some other works, WT-based DEIS has been applied to batteries during charge–discharge [21] and to fuel cells under step-current [22], using multi-sine perturbation signals. However, this method is invalid at low frequencies because the multi-sine injection contains only one or two cycles of low-frequency components, and WT-induced frequency leakage—caused by end effects, where the wavelet cannot fully expand over a short signal, and spectral aliasing due to too few cycles—leads to significant errors in estimating low-frequency processes.

In summary, a significant research gap remains in the DEIS analysis of PEMWE:

1. **Extraction of accurate impedance during dynamic processes:** Existing techniques cannot reliably extract impedance information under transient current conditions, where an error margin generally within $\pm 5\%$ is required for meaningful analysis [23].
2. **Separation of AC and DC information:** Adequate decoupling of AC perturbations from the DC baseline

under dynamic conditions is still limited, directly affecting the ability to characterize how transient processes influence the perturbation injection point.

3. **Coverage of a wide-band frequency range (millihertz to kilohertz):** Most current DEIS approaches lack sufficiently broad frequency coverage. For PEMWE diagnostics, a bandwidth spanning 10 *m*Hz to 5 *k*Hz is generally required to fully resolve both low-frequency mass transport phenomena and high-frequency ohmic contributions.

Addressing these limitations is essential for achieving accurate and operando-relevant impedance characterization in PEMWE systems. Hence, a clear need exists for an extraction method that can provide accurate DEIS information over a wide frequency range — from the millihertz to the kilohertz for PEMWEs — in order to facilitate the practical implementation of dynamic EIS in real-world applications.

Some other methods can potentially extract the instantaneous amplitude and phase of a signal, enabling the acquisition of DEIS. The Hilbert–Huang transform (HHT), proposed in [24], can analyze nonlinear and nonstationary signals and has been applied in power system control to study signals under faulty conditions [25]. The quadrature demodulation transform (QDT) can convert an AC signal to a DC signal and is commonly used in phase-locked loops (PLL) for converter control [26]. Although these methods offer distinct advantages, they have rarely been applied in DEIS calculations.

Therefore, based on the existing analysis methods and considering the characteristics and limitations of each one, this paper proposes a hybrid method to obtain DEIS curves of PEMWEs under dynamic operating conditions. The main contributions of this work include:

- Theoretical contribution: In this work, the concept of DEIS is formally defined, and five impedance estimation methods—FFT, WT, STFT, HHT, and QDT—are systematically introduced, with a detailed comparison of their working principles, computational complexity, and accuracy. Their limitations for EIS extraction under dynamic operating conditions are also highlighted. Furthermore, for the first time, QDT and HT are introduced into DEIS calculation, offering new methodological avenues for future research.
- Methodological contribution: A hybrid approach is proposed, in which the time-varying signals are segmented into three parts according to their local characteristics. Different impedance estimation methods are selectively applied to quasi-linear and nonlinear regions, thereby ensuring adaptive and robust DEIS extraction throughout the entire measurement duration. Experimental results demonstrate that the proposed strategy achieves DEIS calculation errors below 0.2% across a range of simulation scenarios.
- Experimental validation: In addition to simulation validation using an RC equivalent circuit model, the realistic output power of a photovoltaic (PV) system is used as the power input to the PEMWE, enabling the acquisition of DEIS under dynamically varying real-world environmental conditions. An error metric is defined to quantify the calculation errors of the proposed hybrid method, showing that the approach maintains errors below 4% in both simulation and experimental validations.

The remainder of this paper is organized as follows: Section 2 presents several typical methods for extracting signal amplitude and phase. The proposed hybrid method is described in Section 3. Section 4 presents the simulation and experimental validations, followed by the conclusions in Section 5.

2. Dynamic electrochemical impedance spectroscopy measurement methodology

2.1. DEIS Fundamentals

Electrochemical impedance spectroscopy (EIS) is a technique used to measure the response of an electrochemical system to a small-amplitude alternating current (AC) voltage or current over a range of frequencies, enabling the analysis of processes such as charge transfer, mass transport, and electrode/electrolyte interface behavior [27]. To obtain a complete EIS spectrum, a perturbation signal (either current or voltage) covering a wide frequency range is applied to the system.

In conventional EIS, the system is assumed to operate under steady-state conditions. However, under dynamic operating conditions, the amplitude and phase of both the perturbation and response signals become time-varying.

Considering an electrolyzer as a test object, in galvanostatic mode, the AC excitation signal $i_{ac}(t)$ with the angular frequency ω is added to a time-varying base signal $i_{base}(t)$ as:

$$i_{tot}(t) = i_{base}(t) + i_{ac}(\omega, t) \quad (1)$$

where $i_{tot}(t)$ is the total current applied to the electrolyzer. The corresponding response voltage $v_{tot}(t)$ is expressed as:

$$v_{tot}(t) = v_{base}(t) + v_{ac}(\omega, t) \quad (2)$$

where $v_{ac}(\omega, t)$ and $v_{base}(t)$ denote respectively the AC component corresponding to ω and the remaining part. The output voltage $v_{tot}(t)$ can also be considered as a function of the input current reflecting the electrolyzer operation, as:

$$v_{tot}(t) = f_{ele}(i_{tot}, \theta) \quad (3)$$

where θ is the function parameters. When the AC component $i_{ac}(\omega, t)$ remains relatively small ($|i_{ac}(\omega, t)| \leq 0.1i_{base}(t)$), the linearity of (3) is respected as:

$$v_{tot}(t) = f_{ele}(i_{base}(t), \theta) + f_{ele}(i_{ac}(\omega, t), \theta) \quad (4)$$

When the spectral content of $i_{base}(t)$ near the excitation frequency is much smaller than $i_{ac}(\omega, t)$, it is considered that the AC component of the excitation frequency only appears in $i_{ac}(\omega, t)$. The corresponding AC voltage $v_{ac}(\omega, t)$ can thus be expressed as a function of $i_{ac}(\omega, t)$, as:

$$v_{ac}(\omega, t) = f_{ele}(i_{ac}(\omega, t), \theta) \quad (5)$$

In this case, the corresponding impedance, i.e., DEIS, can be determined from the AC parts, i.e., $v_{ac}(\omega, t)$ and $i_{ac}(\omega, t)$, of the sampled voltage and current signals as follows:

$$\underline{Z}(\omega, t) = \frac{\underline{V}_{ac}(\omega, t)}{\underline{I}_{ac}(\omega, t)} \quad (6)$$

where $\underline{Z}(\omega, t)$, $\underline{V}_{ac}(\omega, t)$, and $\underline{I}_{ac}(\omega, t)$ represent the complex forms of impedance, AC voltage, and AC current, respectively, at time t . In the following, variables with an underline denote their complex form. ω is the perturbation angular frequency (rad/s). It can be decomposed into the amplitude and phase components:

$$\underline{Z}(\omega, t) = Am(\omega, t)e^{jPh(\omega, t)} \quad (7)$$

where j is the imaginary unit; $Am(\omega, t)$ and $Ph(\omega, t)$ represent the instantaneous amplitude and phase of the impedance at ω and t , respectively, and can be calculated based on the perturbation and response signals:

$$\begin{aligned} Am(\omega, t) &= Am_v(\omega, t)/Am_i(\omega, t) \\ Ph(\omega, t) &= Ph_v(\omega, t) - Ph_i(\omega, t) \end{aligned} \quad (8)$$

where $Am_v(\omega, t)$, $Am_i(\omega, t)$, $Ph_v(\omega, t)$ and $Ph_i(\omega, t)$ denote the amplitude and phase of the voltage and current perturbations at frequency ω and time t , respectively.

By applying Eq. (8) across the full frequency spectrum under time-varying operating conditions, an impedance spectrum that reflects the system's dynamic behavior can be obtained, i.e., DEIS. The accuracy of the extracted impedance is fundamentally determined by the precision of the amplitude and phase measurements of both the perturbation and response signals. To ensure reliable DEIS spectra, the remainder of this section introduces commonly used signal-processing methods and discusses their respective advantages and limitations.

2.2. Signal Processing Methods

To compare different signal-processing methods, a discrete signal of length N is considered as the input signal, denoted as $x[n]$, $n \in [1, 2, \dots, N]$. By applying five commonly used methods to this signal, the amplitude and phase of the components at the target angular frequency, i.e., ω , can be extracted. In this way, the performance, accuracy, and characteristic behavior of each method can be clearly assessed.

2.2.1. Fast Fourier transform (FFT)

FFT is an algorithm that decomposes a time-domain signal into multiple sinusoidal components of different frequencies, thereby enabling the conversion of the signal between the time domain and the frequency domain. **Owing to its good performance in obtaining the amplitude and phase of steady-state signals, FFT has been adopted as the standard method in conventional EIS calculations.** The FFT extraction used in this study can be summarized by Algorithm 1.

Algorithm 1 FFT-based Amplitude and Phase Extraction

Input: Signal $x[n]$; sampling frequency f_{sam} ; target angular frequency ω

Output: Amplitude Am_{fft} and phase ϕ_{fft} at ω

1: **Calculate frequency index:**

$$k_{\omega} = \frac{N\omega}{2\pi f_{\text{sam}}}$$

2: **Compute FFT:**

$$\underline{X[k_{\omega}]} = \sum_{n=0}^{(N-1)} x[n] e^{-j \frac{2\pi}{N} k_{\omega} n}$$

3: **Extract amplitude:**

$$Am_{\text{fft}} = \frac{2 |\underline{X[k_{\omega}]}|}{N}$$

4: **Extract phase:**

$$\phi_{\text{fft}} = \arg(\underline{X[k_{\omega}]})$$

5: **Return:** $Am_{\text{fft}}, \phi_{\text{fft}}$

A single amplitude and phase are returned for the concerned time series, meaning that the FFT cannot provide time-resolved information. The analyzed signal should be stationary to ensure the accuracy of the extraction results. The main computational cost is brought by the second step, i.e., "2: Computing the FFT". Considering $\log N$ frequencies are concerned, the computational complexity can be expressed by $O(N \log N)$, meaning that as the length of the analyzed signal, i.e., N , increases, the computational cost of FFT analysis grows at a rate proportional to $N \log N$ [28]. Therefore, when extracting the information of a single frequency component, the computational complexity reduces to $O(N)$.

2.2.2. Short-Time Fourier Transform (STFT)

The STFT divides the signal into several overlapping segments using a "window" function, effectively shortening each analyzed portion to improve extraction accuracy for non-stationary signals, as summarized in Algorithm 2. Based on the characteristics of the analyzed signals, different window functions may be selected, such as the "rectangular window", "hann window", "hamming window", etc. Since the "hann window" exhibits relatively low spectral leakage and is therefore more suitable for extracting impedance information, it is adopted in the following analysis. To ensure both accurate frequency resolution and smooth analysis results, the "window" must cover an adequate length of the signal, and a certain degree of overlap between adjacent "window"s is required. In general, the "window" length N_w should span at least one cycle of the perturbation signal, and the overlapping length N_{ol} is typically chosen to be 50–70% N_w . In this work, the N_w is chosen to be one cycle of the perturbation signal, and the overlap is set to $N_{ol} = 0.5N_w$. As the "window" slides along the signal, the local amplitude and phase within each segment can be extracted. Considering the total number of "window"s and the FFT computed within each "window", the computational complexity of the STFT for extracting the single-frequency signal's amplitude and phase can be approximated as $O(N_{stft} \cdot N_w)$, where N_{stft} represents the number of "windows". Generally, STFT typically requires multiple overlapping FFTs, resulting in a practical computational cost that is substantially higher than that of a single FFT, especially for long signals or when high time resolution is required.

Algorithm 2 STFT-based Amplitude and Phase Extraction

Input: Signal $x[n]$; sampling frequency f_{sam} ; target angular frequency ω ;
"window" function $w[n_w]$ for the window with length N_w ; overlapping length N_{ol} ;
"hann window": $w[n_w] = 0.5(1 - \cos(\frac{2\pi n_w}{N_w-1}))$, $0 \leq n_w \leq N_w - 1$
Output: Amplitude Am_{stft} and phase ϕ_{stft} at ω , and location of window m
1: **Compute the number of windows:**

$$N_{\text{stft}} = \frac{N - N_{ol}}{N_w - N_{ol}}$$

2: **Calculate frequency index:**

$$k_\omega = \frac{N_w \cdot \omega}{2\pi \cdot f_{\text{sam}}}$$

3: **for** $m = 1$ **to** N_{stft} **do**

4: **Compute FFT in one window:**

$$\underline{X[m, k_\omega]} = \sum_{n=0}^{(N_w-1)} x[n]w[n-m]e^{-j\frac{2\pi}{N}k_\omega n}$$

5: **Extract amplitude:**

$$Am_{\text{stft}, m} = \frac{2 |\underline{X[m, k_\omega]}|}{N_w}$$

6: **Extract phase:**

$$\phi_{\text{stft}, m} = \arg(\underline{X[m, k_\omega]})$$

7: **Return:** $Am_{\text{stft}, m}, \phi_{\text{stft}, m}, m$

8: **end for**

2.2.3. Wavelet Transform (WT)

WT was first proposed in [29] for analyzing signals using finite-duration, localized waveforms known as wavelets. To realize WT, a mother wavelet is selected and denoted as $\psi_{a,b}(n) = \frac{1}{\sqrt{a}}\psi((n-b)/a)$, where the scale parameter a and translation parameter b control dilation and time shifting, enabling variable time-frequency resolution. WT has been widely adopted for calculating the DEIS of batteries during their charge-discharge processes. The Morlet wavelet ψ is employed to form the mother wavelet, because its Gaussian-windowed sinusoidal form closely matches a sine signal, providing excellent time-frequency localization for accurate amplitude and phase extraction. The corresponding algorithm for extracting the amplitude and phase of a target angular frequency component based on WT is summarized in Algorithm 3. As the wavelet "window" is shifted across each sampling point, a WT is computed at each position, resulting in a total of N transform operations, with each operation having a computational cost of $O(N)$. Consequently, the computational complexity of the WT-based method for extracting the amplitude and phase at fix frequency the can be approximated as $O(N^2)$.

2.2.4. Hilbert-Huang Transform (HHT)

The HHT combines the Hilbert Transform with empirical mode decomposition (EMD) to extract the instantaneous amplitude and phase of nonlinear and nonstationary signals. EMD decomposes a signal into a set of intrinsic mode functions (IMFs) representing different frequency components, along with a residual term. The Hilbert transform is applied to the IMF corresponding to the target frequency component to calculate its instantaneous amplitude and phase. The calculation steps are summarized in Algorithm 4.

During the process, an instantaneous-phase-based filter is applied to all IMFs to extract the amplitude and phase of the signal at the desired frequency. Hence, the accuracy of IMFs $x_i[n]$ determines the accuracy of the results, which mainly depends on the number of iterations S employed during the EMD computation and is also influenced by the noise present in the signal $x[n]$. Insufficient iterations may result in IMFs that are incompletely extracted and contain low-frequency components, while excessive iterations can introduce spurious modes or cause over-decomposition,

Algorithm 3 WT-based Amplitude and Phase Extraction

Input: Signal $x[n]$; sampling frequency f_{sam} ; target angular frequency ω ;
mother wavelet function ψ and its center frequency f_{cen} ;
Morlet wavelet: $\psi(t) = \frac{1}{\sqrt[4]{\pi}} e^{2\pi j f_{cen} t} e^{-t^2/2}$

Output: Amplitude Am_{wt} and phase ϕ_{wt} at ω , and time t

1: **Compute the scaling factor**

$$a_\omega = 2\pi f_{cen} f_{sam} / \omega$$

2: **for** $b = 0$ to $N - 1$ **do**

3: **Compute WT:**

$$\underline{W(a_\omega, b)} = \frac{1}{\sqrt{a_\omega}} \sum_{n=0}^{N-1} x[n] \psi\left(\frac{n-b}{a_\omega}\right)$$

4: **Compute the time:**

$$t[n] = b / f_{sam}$$

5: **Extract amplitude:**

$$Am_{wt}(\omega, t) = |\underline{W(a_\omega, b)}|$$

6: **Extract phase:**

$$Ph_{wt}(\omega, t) = \arg(\underline{W(a_\omega, b)})$$

7: **Return:** $Am_{wt}(\omega, t)$, $\phi_{wt}(\omega, t)$, $t[n]$

8: **end for**

leading to signal distortion and high computational complexity. In practical applications, the sifting number S is typically chosen in the range of 5–8. In this study, $S = 8$ and additional judgment step is incorporated to avoid over-decomposition. For a single-frequency signal of length N , the computational overhead introduced by EMD is on the order of $O(SN)$.

2.2.5. Quadrature Demodulation Transform (QDT)

QDT offers an efficient means of extracting amplitude and phase at a known frequency, which could be suitable for the EIS extraction case [30]. It uses a set of orthogonal signals to demodulate the AC components at target angular frequency ω into a DC signal that encodes amplitude and phase information, which is subsequently extracted by a low-pass filter (LPF). Corresponding steps are shown in Algorithm 5. To guarantee accurate extraction, the LPF must attenuate more than 95% of the ω components present in the constructed orthogonal vectors. To achieve the desired filtering in this work, two first-order LPFs, which have lower computational cost than higher-order filters, are connected in series. The attenuation rate of the combined filter can be expressed as: $1 - 1/\sqrt{1 + (\omega/\omega_c)^2}$, where ω_c is the cut-off frequency of the first-order LPF. In this study, it is set to $\omega/5$ to ensure effective filtering. And the filtering stage contributes the major part of the computational cost. The computational complexity resulted by the employment of the LPF for a signal of length N is given by $O(N)$.

2.3. Simulation Comparison

To compare the accuracy of the five methods described above, a time-varying DC signal is constructed in (9), where the DC signal, which varies relatively rapidly over time at a rate of 1 unit/s, is employed to model the variation of the operating point. Considering that the electrolyzer typically operates above 10 A in practice to maintain efficiency, the initial value of the simulated DC signal is set to 10. The reference signal, comprising both AC and DC components, is presented as follows:

$$x_{ref}(t) = x_{dc} + k_{per} x_{dc} \cos(\omega t + 0.3\pi) \quad (9)$$

where x_{dc} represents a time-dependent DC signal and ω denotes the target angular frequency, respectively. The amplitude of the AC component is equal to k_{per} of that of DC instantaneously to satisfy the dependence of AC

Algorithm 4 HHT-based Amplitude and Phase Extraction

Input: Signal $x[n]$; sampling frequency f_{sam} ; target angular frequency ω ;

the number of iteration S

Output: Amplitude Am_{ht} and phase ϕ_{ht} at ω , and time t

```
1: Set the initial value of residual and the order of IMFs:  $x_r[n] = x[n]$ ;  $M = 1$ 
2: while  $x_r[n]$  is not monotonic do
3:    $h[n] = x_r[n]$ 
4:   for  $s = 1$  to  $S$  do
5:     Find extrema of  $h[n]$  and record its number:  $Num_{ex}$ 
6:     Compute upper envelope via spline interpolation:  $En_{upper}[n]$ 
7:     Compute lower envelope via spline interpolation:  $En_{lower}[n]$ 
8:      $m[n] = (En_{upper}[n] + En_{lower}[n])/2$ 
9:     Compute the number of the zero-crossing count:  $Num_{zc} = \text{number of times "h(m)h(m+1) < 0, 0 < m < n"}$ 
10:    if  $m[n] \approx 0$  and  $|Num_{zc} - Num_{ex}| \leq 1$  then
11:      Break the "for" cycle;
12:    end if
13:     $h[n] = h[n] - m[n]$ 
14:  end for
15:  Compute the M-th order IMF:  $x_M[n] = h[n]$ ;  $r[n] = r[n] - h[n]$ ;  $M = M + 1$ 
16: end while
```

$$x[n] = \sum_{i=1}^M x_i[n] + x_r[n]$$

```
17: for all  $i \leq M$  do
```

```
18:   Compute the Hilbert transform of  $x_i[n]$ 
```

$$\hat{x}_i[n] = (x_i * h_i)[n]$$

$$h_i[n] = \begin{cases} \frac{2}{n\pi}, & n = \pm 1, \pm 3, \pm 5, \dots \\ 0, & n = 0, \pm 2, \pm 4, \dots \end{cases}$$

```
19:   Compute the angular frequency:
```

$$\omega_{cal} = \frac{\phi_{ht-i}[n+1] - \phi_{ht-i}[n-1]}{2/f_{sam}}$$

$$\phi_{ht-i}[n] = \arg\left(\frac{\hat{x}_i[n]}{x_i[n]}\right)$$

```
20:   if  $\omega_{cal} = \omega$  then
```

```
21:     Compute time:
```

$$t[n] = n/f_{sam}$$

```
22:     Extract amplitude:
```

$$Am_{ht-i}[n] = \sqrt{x_i^2[n] + \hat{x}_i^2[n]}$$

```
23:     Return:  $Am_{ht-i}[n], \phi_{ht-i}[n], t[n]$ 
```

```
24:     Break the "for" cycle;
```

```
25:   end if
```

```
26: end for
```

Algorithm 5 QDT-based Amplitude and Phase Extraction

Input: Signal $x[n]$; sampling frequency f_{sam} ; target angular frequency ω ;

Output: Amplitude Am_{qdt} and phase ϕ_{qdt} at ω , and time t

1: **Compute time:**

$$t[n] = n/f_{\text{sam}}$$

2: **Construct orthogonal vectors:**

$$x_d[n] = x[n] \cdot \cos(\omega \cdot t[n])$$

$$x_q[n] = x[n] \cdot \sin(\omega \cdot t[n])$$

3: **Select the cutoff frequency of low-pass filter:**

$$\omega_c = \omega/5$$

4: **Extract the orthogonal DC component:**

$$X_d = \text{LPF}(x_d, \omega_c)$$

$$X_q = \text{LPF}(x_q, \omega_c)$$

5: **Extract amplitude:**

$$Am_{qdt}[n] = 2 \cdot \sqrt{X_d[n]^2 + X_q[n]^2}$$

6: **Extract phase:**

$$\phi_{qdt}[n] = \arctan\left(\frac{X_q[n]}{X_d[n]}\right)$$

7: **Return:** $Am_{qdt}[n], \phi_{qdt}[n], t[n]$

amplitude on DC component in EIS implementation. An initial phase between -0.5π and 0.5π is assigned to enhance the generality of the comparison results.

To ensure consistency with subsequent experimental validation, the simulations were conducted using the same sampling rate as the experimental setup (i.e., 50 kHz). The perturbation duration was set to 10 cycles. Under a linearly varying DC signal with a slope of 1, defined as $x_{dc} = 10 + t$, a 1 Hz AC signal was superimposed with an amplitude equal to 10% of the DC component (i.e., $k_{per} = 0.1$). The reference signal is shown as the black curve in Figure 1, indicating that the DC component increases by 100% relative to its initial value during the perturbation period. Based on the five methods, the amplitude and phase of the simulated signal are extracted, and the corresponding reconstructed signals are also generated using the extracted information presented as the red lines in Figure 1. The results indicate that the FFT exhibits the poorest extraction performance for non-stationary signals, as illustrated in Figure 1 (a). This limitation arises because the FFT analyzes the entire measurement signal simultaneously, yielding only the average amplitude and phase over the full duration of the signal. In contrast, the STFT performs segmentation of the signal by adding a "hann window" function, allowing the estimation of the average amplitude and phase within each localized time segment, thereby reducing the overall error. However, the fixed window length still introduces residual errors within each segment, displayed as indicated in Figure 1 (b). The WT employs translatable and scalable windows to adaptively determine the analysis region, resulting in a significant improvement in extraction accuracy. Nonetheless, the influence of boundary effect leads to larger errors near the beginning and end of the signal as shown in Figure 1 (e). The HHT demonstrates the most accurate extraction performance for ideal, noise-free signals, as depicted in Figure 1 (c). In contrast, QDT indicated in Figure 1 (d) exhibits considerable errors at the initial stage of the signal due to the effect of the incorporated LPF.

To evaluate and compare the performance of different methods, we define the maximum error and average error between the extracted and reference signals, along with the computational time required by each method under

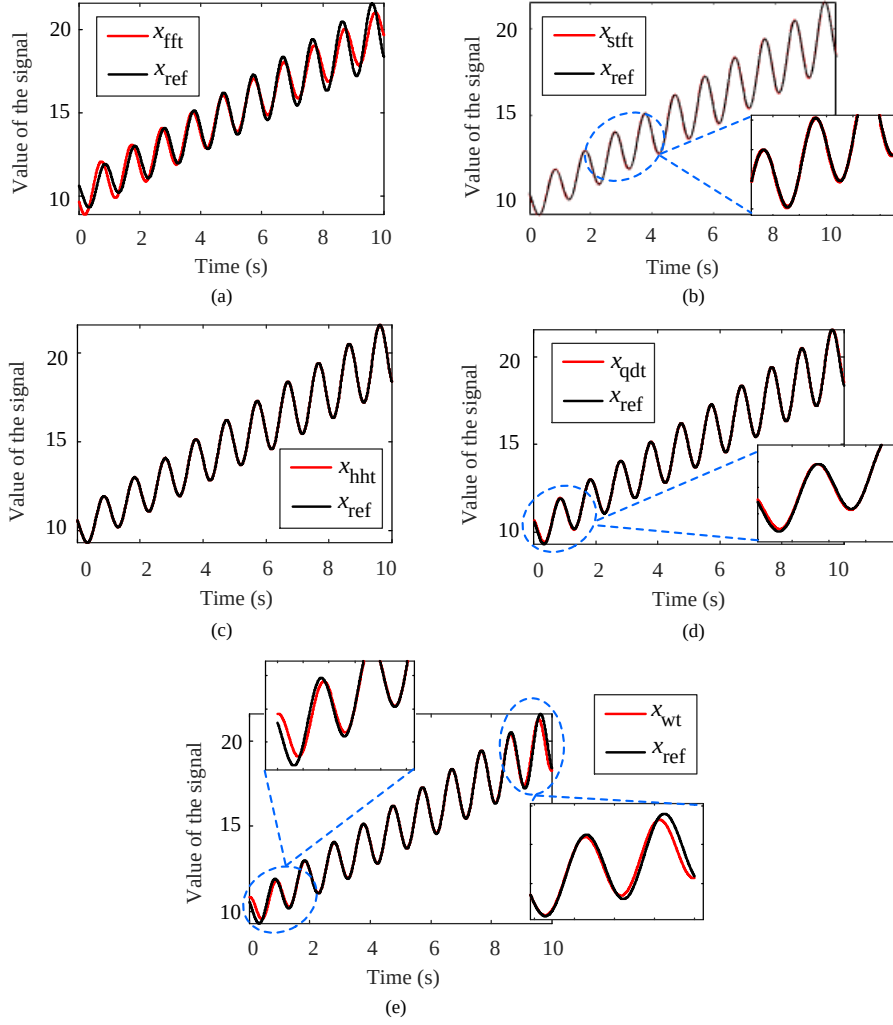


Figure 1: Comparison of five different methods: (a) FFT, (b) STFT, (c) HT, (d) QDT, (e) WT.

identical hardware and software configurations. The formal definitions are provided below.

$$\begin{aligned} \text{Maximum error: } E_{\max} &= \max(|x_{\text{extract}} - k_{\text{per}} x_{\text{dc}} \cos(\omega t + 0.3\pi)| / k_{\text{per}} x_{\text{dc}} \cos(\omega t + 0.3\pi)) \\ \text{Average error: } E_{\text{ave}} &= \text{mean}(|x_{\text{extract}} - k_{\text{per}} x_{\text{dc}} \cos(\omega t + 0.3\pi)| / k_{\text{per}} x_{\text{dc}} \cos(\omega t + 0.3\pi)) \end{aligned} \quad (10)$$

To ensure reliability and facilitate a comprehensive comparison, simulations were conducted under a variety of conditions. These included both linear ($x_{\text{dc}} = 10 + t$) and nonlinear ($x_{\text{dc}} = \max(t) \log(1 + 9 * t / \max(t)) / \log(10)$) DC variations, fundamental frequencies of 1, 10, and 100 Hz, and the addition of Gaussian noise (Signal-to-Noise Ratio = 40 dB). The variation rate represents the drift of the DC current at the injection point compared to its initial value when start perturbation. Three different variation rates are compared: 100%, 10%, and 1%. Furthermore, AC amplitude levels of 1% and 10% of the DC component were examined to cover scenarios in which the response signal amplitude is small. The simulation results, calculated using (10), are summarized in Table 1 and Table 2. Under ideal conditions (linear and nonlinear conditions without noises), HHT demonstrates superior performance with the highest extraction accuracy in most cases. However, under non-ideal conditions (with Gaussian Noise):

- At low frequencies (1 Hz), WT achieves the highest precision for both 1% and 10% AC amplitudes, albeit at the cost of the highest computational latency.

- At intermediate frequencies (10 Hz), both WT and QDT show robust accuracy, though QDT is significantly more time-efficient.
- At high frequencies (100 Hz), FFT remains highly effective with minimal computational overhead. This is attributed to the shortened measurement window at high frequencies, where DC variations become negligible, allowing the system to be treated as operating at a steady-state point.

In summary, there is a clear trade-off between accuracy and computational time among the different algorithms. Based on the simulation results, a comprehensive comparison of all analysis methods are summarized in Table 3.

Table 1: Simulation results of signal extraction errors and computational time for different algorithms, with $k_{per} = 10\%$.

f (Hz)	Signal type	Metric	FFT	STFT	WT	HHT	QDT	Variation
1	Linear	E_{max} (%)	102.17	8.60	1.10	0.16	1.14	100%
		E_{ave} (%)	28.48	2.77	0.68	0.05	0.36	
	Nonlinear	E_{max} (%)	108.44	9.26	1.46	0.34	1.50	
		E_{ave} (%)	28.02	2.81	0.76	0.08	0.39	
	Linear + Noise	E_{max} (%)	102.17	8.65	1.09	11.23	2.98	
		E_{ave} (%)	28.48	2.77	0.67	3.62	0.78	
	Computational time (s)		0.8349	0.9670	5.959	0.8503	0.8456	
10	Linear	E_{max} (%)	9.17	0.82	1.41	0.01	3.80	10%
		E_{ave} (%)	2.93	0.31	0.87	0.03	0.94	
	Nonlinear	E_{max} (%)	9.85	1.00	1.47	0.01	3.64	
		E_{ave} (%)	2.84	0.31	0.90	0.04	0.90	
	Linear + Noise	E_{max} (%)	9.17	1.49	1.48	12.92	2.51	
		E_{ave} (%)	2.93	0.40	0.88	6.62	0.74	
	Computational time (s)		0.7887	0.8648	1.5050	0.8261	0.8278	
100	Linear	E_{max} (%)	2.07	1.32	0.45	<0.01	4.16	1%
		E_{ave} (%)	0.83	0.81	0.26	<0.01	1.04	
	Nonlinear	E_{max} (%)	2.11	1.33	0.45	<0.01	4.15	
		E_{ave} (%)	0.82	0.81	0.26	<0.01	1.03	
	Linear + Noise	E_{max} (%)	2.07	3.67	0.70	4.46	3.94	
		E_{ave} (%)	0.83	0.94	0.28	1.41	1.08	
	Computational time (s)		0.7866	0.8586	0.9197	0.8220	0.8208	

3. Hybrid extraction method

According to the characteristics of all the methods introduced in Section 2.2, including their computational complexity and accuracy, and with the consideration of the type of the perturbation signal for the PEMWE during the EIS implementation, a hybrid method for DEIS extraction is proposed in this section.

3.1. Theoretical basis of the proposed method

Using sequential sinusoidal signals in EIS implementation can avoid the effects of frequency aliasing, thereby ensuring the accuracy of the calculated impedance during EIS implementation. Therefore, it is selected as the perturbation signal type in our study, and both the perturbation and response signals can be analyzed based on partitioned frequency components. During DEIS implementation, based on the variation in the locations of the injection points at each frequency, the sampled signals are divided into quasi-steady-state and non-steady-state regions, as shown in Figure 2. Within the non-steady-state region, the signal is further divided into low- and high-frequency regions to ensure the accuracy of the extracted information. For each region, an appropriate extraction method is employed, with further details given in the following:

Table 2: Simulation results of signal extraction errors and computational time for different algorithms, with $k_{per} = 1\%$.

f (Hz)	Signal type	Metric	FFT	STFT	WT	HHT	QDT	Variation
1	Linear	E_{max} (%)	102.17	8.60	2.42	5.52	2.28	100%
		E_{ave} (%)	28.48	2.77	0.75	1.22	0.60	
	Nonlinear	E_{max} (%)	108.44	9.26	1.85	4.39	9.57	
		E_{ave} (%)	28.02	2.81	0.72	1.95	2.13	
	Linear + Noise	E_{max} (%)	102.17	9.34	2.31	104.51	49.55	
		E_{ave} (%)	28.48	2.86	0.76	33.23	19.36	
	Computational time (s)		0.8349	0.9670	5.959	0.8503	0.8456	
	10	Linear	E_{max} (%)	9.17	0.82	1.41	0.28	
E_{ave} (%)			2.93	0.31	0.87	0.11	0.79	
Nonlinear		E_{max} (%)	9.85	1.00	1.47	0.81	4.34	
		E_{ave} (%)	2.84	0.31	0.90	0.18	0.88	
Linear + Noise		E_{max} (%)	9.17	5.94	2.47	36.51	2.94	
		E_{ave} (%)	2.93	2.06	1.22	8.90	1.06	
Computational time (s)		0.7887	0.8648	1.5050	0.8261	0.8278		
100		Linear	E_{max} (%)	2.07	1.32	0.45	< 0.01	4.12
	E_{ave} (%)		0.83	0.81	0.26	< 0.01	1.03	
	Nonlinear	E_{max} (%)	2.11	1.33	0.45	0.02	3.80	
		E_{ave} (%)	0.82	0.81	0.26	0.05	0.95	
	Linear + Noise	E_{max} (%)	2.07	19.68	10.86	24.39	13.94	
		E_{ave} (%)	0.83	7.08	5.74	10.77	6.54	
	Computational time (s)		0.7866	0.8586	0.9197	0.8220	0.8208	

Table 3: Comparison of different analyzing methods

Methods	Localization	Signal Type	Computational complexity	Amplitude and phase	
				Accuracy in non-steady state	Key influencing factors
FFT	Frequency	Stationary	$O(N \log N)$	Poor	Sampling frequency, lngth of the signal
STFT	Time and frequency	Non-stationary	$O(Num_{w-stft} \cdot N_w \log N_w)$	Moderate	Sampling frequency, length of the signal, the number of windows
WT	Time and frequency	Non-stationary	$O(N^2)$	High	Sampling frequency, length of the signal, mother wavelet function
HHT	Instantaneous phase and amplitude	Non-stationary and transient	$> O(SN)$	Scenario-dependent High	Sampling frequency, length of the signal, noise of the signal
QDT	Instantaneous phase and amplitude	Non-stationary and transient	$O(N)$	High	Sampling frequency, known frequency, accuracy of the LPF

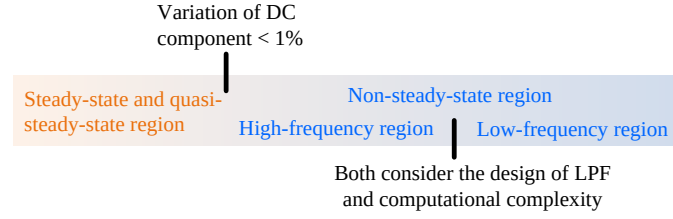


Figure 2: The separation of the region.

- **Quasi-steady-state region:** In this region, both the perturbation and response signals can be regarded as stationary. FFT is advantageous here, as it can quickly provide accurate amplitude and phase information. Changes in operating conditions leads to variations in both the output current and voltage, with the current of the PEMWE exhibiting more pronounced fluctuations. Therefore, the current variation is used as the criterion to distinguish between the quasi-steady-state and non-steady-state regions. Ensuring that the relative error of the extracted signal at target frequency based on FFT is below 5% guarantees that the resulting EIS error also remains below 5%, thus satisfying the *IEC 62282-7-1*. Using the FFT error expression for the fundamental component under linear DC drift, it is determined that, in order to meet the above standard, the DC drift over the measurement period should not exceed 1.57% of the nominal DC component. Hence, in this study, when the variation of the DC component is smaller than 1% within each frequency segment of the perturbation signal, the system can be considered to be operating under quasi-steady-state conditions.
- **Non-steady-state region:** In the non-steady-state region, the perturbation and response signals are non-stationary. Based on the characteristics of the methods, the region is further separated into low-frequency and high-frequency sub-regions.
 - **Low-frequency region:** The low frequency of the perturbation and response signals allows sufficient sampling data to ensure adequate frequency resolution. However, both designing a filter that can accurately extract the DC component for the QDT method and separating low-frequency perturbation/response signals and DC components for the HHT method remain challenging. Consequently, WT is the most suitable method for extracting the real-time amplitude and phase in this region, as its accuracy depends on the proper selection of scale and translation parameters, which is supported by sufficient sampling data.
 - **High-frequency region:** In contrast to the low-frequency region, the signals in the high-frequency region cannot achieve sufficient frequency resolution due to the sampling limitations. In theory, both QDT and HHT can be used to extract the impedance information. However, HHT involves relatively complex computations, and the noise contained in the IMFs can cause significant errors in phase estimation. It is not selected for the impedance extraction in our study. In contrast, QDT features simpler computations. As described in Algorithm 5, step "2: Construct orthogonal" converts the noises into higher-frequency components. Moreover, the LPF in step "4: Extract the orthogonal DC component" not only extracts the orthogonal DC components but also reduces the influence of noise, making QDT more appropriate in this region.

The selection of the boundary frequency separating two regions, in this region, considers both the characteristics of the selected algorithms and the properties of the perturbation signals. As introduced in Section 2, the QDT method requires the design of an LPF, which introduces a non-negligible time delay. To avoid impedance-extraction errors caused by this delay, it is common practice to discard the portion of the signal affected by the filter's transient response. For example, the LPF used in our work consists of two first-order LPFs connected in series, each with a cutoff frequency of $0.2 \cdot \omega$. Under these conditions, at least two cycles are typically required to obtain a DC signal with 95% accuracy, meaning that the first two cycles must be discarded. In practical measurements, to shorten the measuring time and reduce storage requirements, the number of cycles is adjusted according to the perturbation signal frequency. Low-frequency signals are assigned fewer cycles—generally no more than 10—especially when millihertz-range signals are involved, where the number of cycles may be fewer

than 6. Referencing the cycle-selection principles used in commercial EIS equipment (e.g., Zahner), we set the number of cycles to 6 for signals below 10 Hz and to 30 for those above 10 Hz. To ensure a sufficient number of valid cycles (more than 5 cycles) for both algorithmic analysis and impedance extraction, the boundary between the low- and high-frequency regions is set to 10 Hz in this work.

3.2. Simulation verification based on the fixed-parameter ECM

Given that the internal relaxation processes in PEMWEs correspond to several equivalent $R//C$ circuits, an ECM for the tested PEMWE was constructed using fixed parameter values to verify the effectiveness of the proposed hybrid method, as shown in Figure 3. The ECM is composed of three parallel $R//C$ sub-circuits connected in series with a single series resistor, representing the different relaxation processes of the PEMWE as discussed in Section 4. The corresponding parameter values are assigned according to those identified at the fixed injection point of 31.25 A, as listed in Table 4.

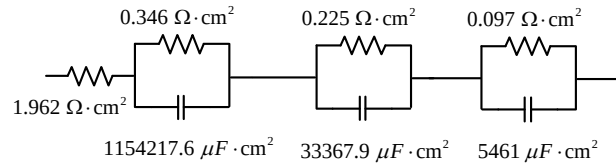


Figure 3: ECM and corresponding fixed parameters.

To obtain the complete impedance response, the frequency of the perturbation signal must cover the characteristic frequencies of all sub-circuits, which can be calculated by $f_{cha} = 1/2\pi RC$. For the three sub-circuits in Figure 3, the characteristic frequencies are approximately 0.39 Hz, 21.2 Hz, and 300 Hz, respectively. Therefore, in the simulation and the subsequent validation section, the frequency range of the perturbation signal is set from 0.01 Hz to 5 kHz to ensure full spectral coverage. Considering both the measurement duration and the efficient operating-current range of the PEMWE used in the platform (i.e., 10–50 A), a DC current signal with an increasing rate of 0.1 A/s and an initial value of 10 A is applied to the ECM in the simulation. The sampled current waveform containing both the DC component and the perturbation signal and corresponding response voltage signal are illustrated in Figure 4.

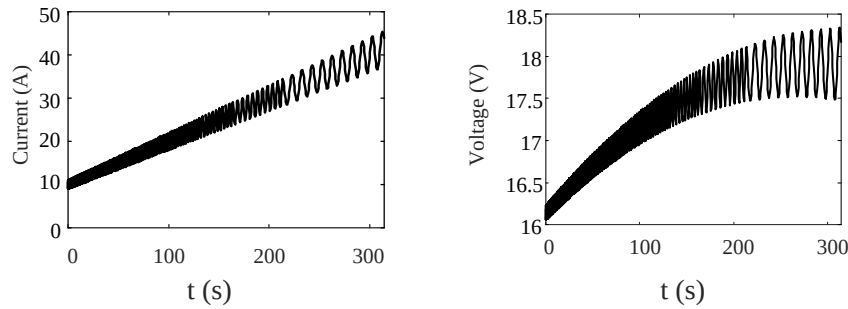


Figure 4: Perturbation and response signals: (a) perturbation current signal; (b) response voltage signal.

It is evident that both the current and voltage in Figure 4 vary significantly over the measurement period. Therefore, the system cannot be considered in steady state, and classical EIS measurements are not applicable. Using the proposed hybrid method, the amplitudes and phases of the perturbation and response signals are extracted. Based on (8), the DEIS results of the RC circuit model are presented in a Bode-type representation, as indicated in Figure 5. In the DEIS analysis, in addition to the impedance information, the operating condition—variable DC current at injection point—is also presented.

To evaluate the accuracy of the hybrid method for calculating the DEIS, a relative error is defined. To account for

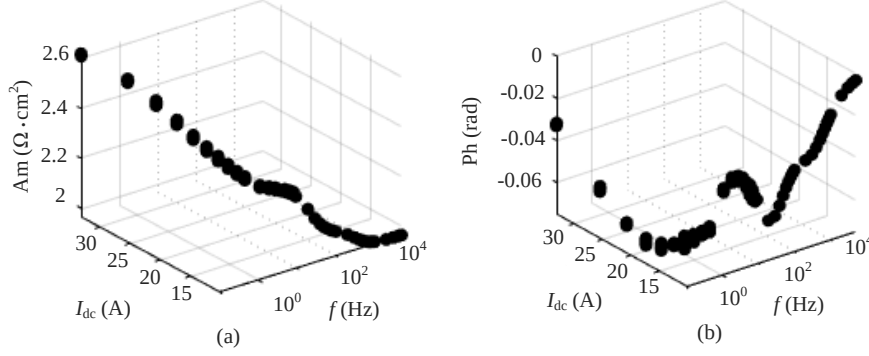


Figure 5: DEIS for RC circuit model in Bode representation.

both amplitude and phase errors, the complex form in (7) is used:

$$\epsilon_z = \frac{|Z_{cal}(\omega) - Z_{ref}(\omega)|}{|Z_{ref}(\omega)|} \times 100\% \quad (11)$$

where $Z_{cal}(\omega)$ and $Z_{ref}(\omega)$ represent the calculated impedance based on the hybrid method and the theoretical impedance, respectively. The corresponding error between the impedance calculated using the proposed method and the theoretical value of the fixed RC circuit, denoted as ϵ_{z-RC} , is evaluated and presented in Figure 6. Since both the QDT and WT calculate instantaneous values, a set of values is obtained at each frequency, as depicted by the gray circles in Figure 6. Additionally, as the selected model is a fixed RC circuit whose impedance remains unaffected by the DC current at the injection point, the maximum value is highlighted with a blue line to represent ϵ_{z-RC} , showing the proposed method maintains an error below 0.2% over the full frequency range when extracting the impedance spectrum of the fixed-parameter ECM.

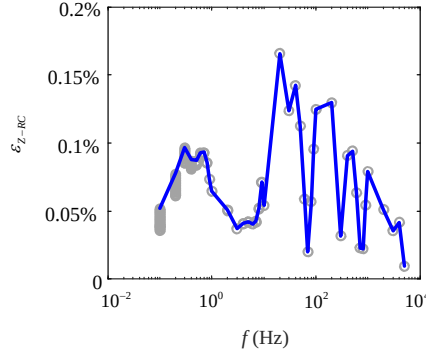


Figure 6: Errors between DEIS and the actual values.

4. Validation under real-world power conditions

To verify the efficiency and the accuracy of the proposed method in real-world applications, the power generated by a PV system is used as the input of the electrolyzer to simulate real operating power variations. A publicly available dataset of output power from March 03, 2025, provided by Elia [31], is selected and is shown in Figure 7. It includes data on the output power in Belgium from 0:00 AM to 11:59 PM. Corresponding simulation and experimental studies are conducted in this section, with the EIS implementation starting at 10:00 AM, when the output power is 632.4 W.

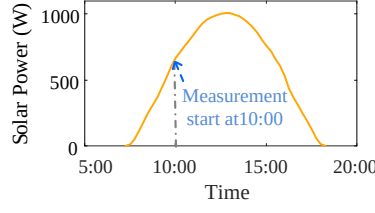


Figure 7: Output power of a PV system (extracted from a public dataset [31]).

4.1. Simulation based on the ECM with variable parameters

To simulate the characteristics of the PEMWEs, a simplified ECM is established based on the approach described in [5], as shown in Figure 8 (a). In the ECM, each sub-circuit represents a specific physical process occurring during electrolysis:

- $R_1//C_1$ models the mass transport behavior;
- $R_2//C_2$ corresponds to oxygen evolution reaction process;
- $R_3//C_3$ represents the hydrogen evolution reaction process;
- R_s denotes both the proton transfer process and the connection resistance within the system.

Table 4: Equivalent parameters of ECM

I_{dc}	R_s	R_{p1}	C_{p1}	R_{p2}	C_{p2}	R_{p3}	C_{p3}
31.25	1.962	0.346	1154217.607	0.225	33367.867	0.097	5461.087
37.5	1.932	0.059	1184643.429	0.19	31992.728	0.087	5316.129

$R_s, R_{p1}, R_{p2}, R_{p3}$, units $\Omega \cdot cm^2$;
 C_{p1}, C_{p2}, C_{p3} , units $\mu F \cdot cm^2$;

In the simulation, theoretical ECM parameters at fixed injection points in the simulation are derived from experimental measurements of the PEMWE at $40^\circ C$, 1 bar and a flow rate of 1 L/min, as summarized in Table 4. The two currents cover the range from the start to the stop of EIS implementation. To determine the equivalent circuit parameters at each current point during the injection process, linear interpolation is performed between these two points using MATLAB's *interp1* function. This allows for the simulation of an ECM with variable parameters.

As discussed in the previous section, the perturbation signal must span all characteristic frequencies of the ECM. For the ECM used in this section, shown in Figure 8(a), the characteristic frequency range is 0.3–334 Hz. Hence, the EIS is conducted at 10:00 AM using a sequential frequency perturbation signal ranging from 0.1 Hz to 5 kHz. The total measurement duration is 161 s. Using the hybrid extraction method, the DEIS curve is extracted and presented in the Bode representation, as shown the as the black cycles in the sub-figures in Figure 8, illustrating both the impedance and the operating condition. Corresponding model-based impedance spectrum is calculated and indicated as the blue line in Figure 8 (b). The deviation between the model-based impedance and extracted DEIS are calculated based on (11) and illustrated in Figure 8 (c). The results indicate that the proposed hybrid method achieves an accuracy greater than 99.6%.

4.2. Experimental validation

The experiments are performed on the platform developed in the laboratory as shown in Figure 9. The equivalent PV system output is emulated by controlling a programmable power source (IT-M3900C) via a realtime controller (dSPACE Microlabbox). A wide-band programmable load (Chroma 63200A) is connected in parallel with the power source, enabling perturbation signal injection into the electrolyzer by adjusting the load. Environmental operating

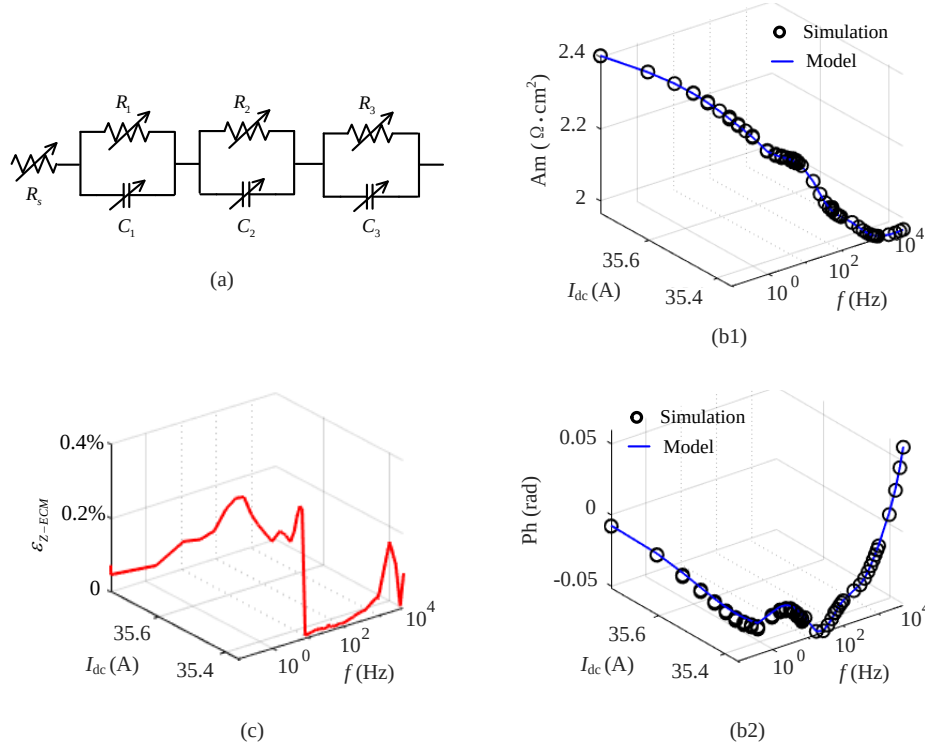


Figure 8: Simulation results: (a) the ECM of the PEMWE in MATLAB/Simulink; (b) DEIS results in Bode representation – (b1) amplitudes and (b2) phases; (c) errors between DEIS results and theoretical values.

conditions are controlled in a steady-state, with a temperature of 40°C , a pressure of 1 bar and a flow rate of 1 L/min . When the perturbation signal is injected, both the current and voltage of the PEMWE are collected. In the experiment, the DC current at the injection point increases from 33.9 A to 36 A, a 6.2% current rise during the EIS implementation period, making it unsuitable for using the classical EIS method.

The impedance is calculated based on the proposed hybrid extraction method and (8), and the corresponding results are presented in Figure 10. Both the impedance information and the operating condition, i.e., current value at injection point, are clearly reflected.

To evaluate the accuracy of the proposed method, an impedance map—obtained by measuring the impedance at each stabilized injection point under identical operating conditions—is regarded as the theoretical impedance of the electrolyzer, as demonstrated in Figure 11. Then the errors between the DEIS results and the theoretical values are quantified using (11). The resulting data, shown in Figure 12 (a), indicate that the deviation is less than 4%.

As shown in Figure 7, the solar output power increases gradually at 10:00. When performing EIS measurements on the electrolyzer at this time, the non-steady-state region emerges at frequencies below 0.1 Hz as illustrated the green markers in Figure 10, consistent with the criteria established in Figure 2. In the quasi-steady-state range, impedance is calculated using the FFT method, and the resulting characteristics can be summarized as follows:

- **Region of decreasing error:** In the region frequency above 800 Hz, the error is most prominent at frequencies above 800 Hz (indicated by the pink shaded area in Figure 12(b)). As the frequency decreases from this threshold, the error initially declines. This is due to the fixed sampling frequency used throughout the experiment; as the target frequency decreases, the number of sampling points per cycle increases. This allows the frequency index to align more precisely with the target frequency—as detailed in Algorithm 1 — thereby improving the accuracy of the calculation.
- **Region of increasing error:** In the region frequency below 800 Hz, the error exhibits an overall upward trend as the frequency continues to decrease (indicated by the blue shaded area in Figure 12(b)). This trend is attributed

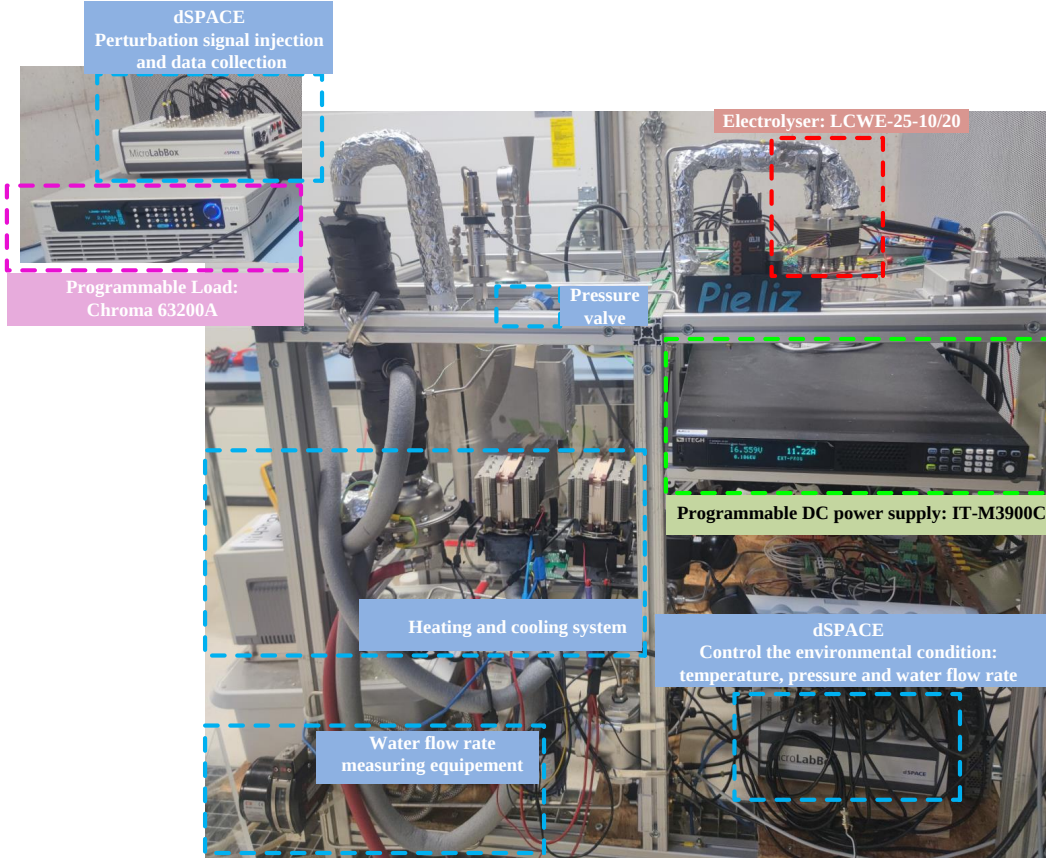


Figure 9: Experimental platform developed in the laboratory FEMTO-ST/FCLAB.

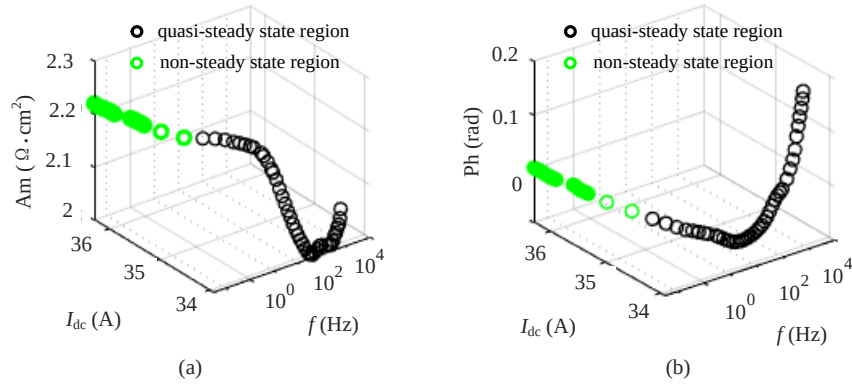


Figure 10: Experimental DEIS results: (a) the amplitudes; (b) the phases.

to the extended measurement durations required for lower frequencies; specifically, the electrolyzer's operating point drifts more significantly within the longer measurement window, leading to increased instability error.

- **Error "peaks":** "Peaks" appear at certain frequency points where the error is notably higher than in the surrounding range. This occurs because the equivalent physical processes of the electrolyzer do not produce a monotonic impedance response; instead, impedance peaks occur at specific characteristic frequencies. These frequencies are the most susceptible to dynamic fluctuations and contain the most pronounced dynamic features. Consequently, as the measurement approaches these characteristic frequencies, the error magnitude increases.

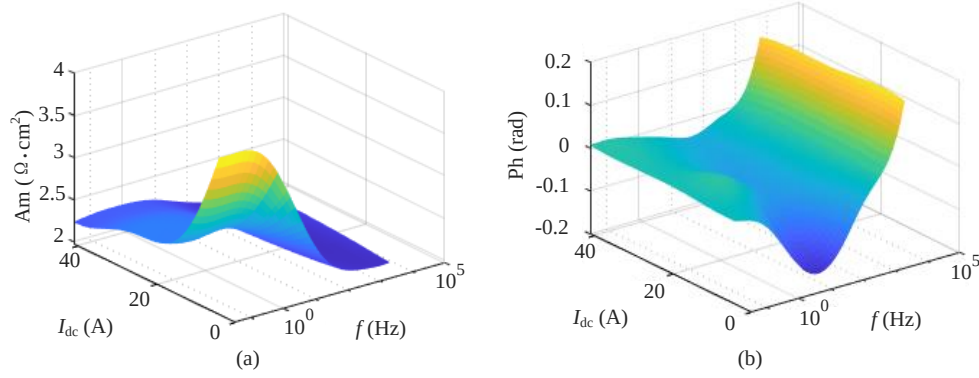


Figure 11: Impedance map under steady-state condition: (a) the amplitudes; (b) the phases.

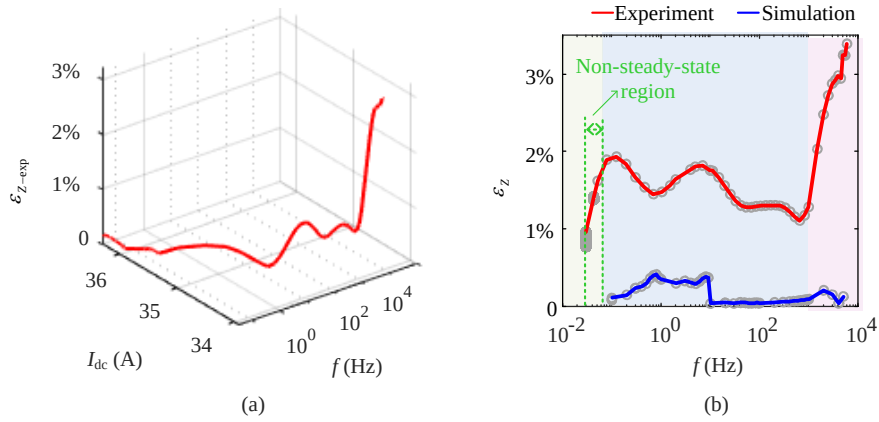


Figure 12: Errors between DEIS results and theoretical values in the experiment: (a) errors in experiment; (b) comparison of the error in experiment and simulation.

Compared with the simulation results of both the fixed RC circuits and the ECM with variable parameters of the electrolyzer, the errors, i.e., ϵ_z observed during the experimental process are greater than those in the simulation as shown in Figure 12 (b). Preliminary analysis suggests that the main sources of the differences are twofold: one is due to the signal processing, since the experimental sampled signals contain significant operational noise that can influence the results; the other is that the real electrolyzer undergoes transient processes (or occurs dynamics) under non-steady-state operating conditions, which are not represented in the current simulation model. In this regard, the error between the measured EIS and the real one should be less than ϵ_z . In future work, deeper analysis will be conducted to distinguish the EIS variation caused by the internal dynamics involved in electrolysis.

5. Conclusion

This paper proposed a hybrid method for obtaining DEIS of PEMWEs under varying operating conditions. By integrating multiple signal analysis techniques, including FFT, WT and QDT, and segmenting signals based on their characteristics, the proposed method effectively overcomes the limitations of existing methods and enables accurate DEIS calculation with lower computational complexity. The methodological effectiveness is substantiated by rigorous quantitative results across multiple contexts. Fixed-parameter simulations achieve an error below 0.2%, while variable ECM simulations based on RC circuits exhibit less than 1% error in tracking dynamic parameter shifts, confirming the method's capability to capture impedance information under varying conditions. The results under experimental conditions shows that the hybrid method achieves DEIS estimation errors below 4% in which demonstrates its validity and effectiveness in the real application.

The experimental results show slight deviations from the simulation, as the ECM does not fully capture the dynamics of the real PEMWEs. The deviation near the characteristic frequencies is notably higher than that of the surrounding frequencies, indicating that the ability of DEIS to reflect the system's dynamics may be limited by the equivalent relaxation processes. In addition, the 10 Hz boundary between QDT and WT was constrained by the limited number of cycles available at different frequencies during our experiments, which in turn increased the computational time of the hybrid methods. Future work will include experiments on PEMWEs under different operating conditions with optimized perturbation cycles to analyze their impacts on the DEIS and to explore the validity boundaries of the DEIS in reflecting the dynamics. Furthermore, the data will be extracted and analyzed from DEIS, providing valuable insights into the transient behavior of internal physical processes and aiming to enhance its applicability for diagnostics.

Acknowledgment

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