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Adaptive finite-time parameter estimation for grid-connected converter with LCL filter

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This study proposes an online finite-time adaptive parameter estimation method for grid-connected voltage source inverter (VSI) with LCL filter. In this framework, a time-continuous state-space system model is first developed, which is different from the nonparametric frequency-response-based method. Then, the parameter estimation error information is extracted by introducing a series of filter operations. Moreover, a sliding mode term is studied and cooperated with the obtained parameter estimation error to design the parameter estimation error-based finite-time adaptive parameter estimation algorithm. With the help of this novel adaptive law, the physical parameters of electrical components can be driven to their true values accurately and fast. Theoretical analysis is conducted in terms of the Lyapunov theory to demonstrate the convergence of the parameter estimation error. Finally, numerical simulation results are provided to illustrate the superiority of the proposed method over the conventional method.

KEYWORDS

adaptive parameter estimation, finite-time convergence, LCL filters, voltage source inverters, parameter identification

1 Introduction

Voltage source inverters (VSIs) are widely implemented in many grid-connected applications due to their capability of converting the DC source to an AC output. In order to convert the current, the inverter is required to implement the pulse modulation technique which will cause high-order harmonic pollution and may trigger a negative impact on grid-connected performance; especially, it may disturb the supply voltage of sensitive loads or devices tied to the grid (Mohamed (2010); Feng et al. (2022)). In order to attenuate the switching frequency harmonics caused by the VSI and improve the quality of the grid capability, a proper filter is needed and implemented between the VSI and the grid practically (Reznik et al. (2013)). Compared with a traditional L-filter (Gomes et al. (2018)), a high-order LCL filter has been generally used in the electrical power system because of its higher attenuation ability and better dynamic characteristics (Tang et al. (2011; 2015)). Moreover, when the range of power levels up to hundreds of kW, the LCL filter can effectively reduce the overall size and weight of the componentswith a small value of inductors and capacitors (Liserre et al. (2005a)).

However, the three-order LCL filter suffers from the resonance problem, which may lead to oscillation of the power grid (Tang et al. (2015)). Although the LCL filter can accommodate the oscillation phenomenon by properly designing the filter parameters (Massing et al. (2011)), some of these parameters may have uncertainties due to the manufacturing tolerances, temperature changes, and the aging of electrical components in practical application. Moreover, if there is a transformer between the filter and the grid, the leakage inductance of the transformer will also lead to uncertainties in the filter (Schlesinger and Biela (2020)), and these lumped uncertainties will impact the overall grid performance.

Since the proper estimation of grid impedance including the LCL filter and VSI has a significant influence on the grid-connected quality, various work based on frequency-response estimation methods (i.e., also known as nonparametric methods) and model-based estimation methods has been done. This kind of method does not assume an exact model and only requires the injected stimulus and the responses. In the work of Liserre et al. (2005b) and Reigosa et al. (2012)), the grid impedance is identified by injecting sinusoidal currents into a grid, in which the Fourier analysis is introduced at a steady state by using the grid-side current and voltage responses. The utilization of sine sweeps provides the highest signal-to-noise ratio (SNR), and thus, it can achieve high-precision identification of the grid impedance. However, this method is not suitable for online identification due to the measurement time and additional power of electronic hardware.

Though frequency-response-based methods are able to describe the dynamic characteristics of the grid, they cannot get the physical parameters of electrical components directly. Furthermore, in many VSI control applications, model-based methods are commonly employed (the controller gains are related as a function of the LCL filter and VSI parameters), such that the prior-knowledge of these uncertain physical parameters is of vital importance. To address the uncertain parameters that existed in electrical power systems, model-based estimation methods are studied in recent years. In (Mohamed and El-Saadany (2008)), the neural networks (NN) based estimation method is proposed, it can obtain great estimation performance, but the NN-based control performance heavily depends on the convergence estimation and rate of NN weights which leads to heavy computational burden. In (Hoffmann and Fuchs (2013)), an extended Kalman filter (EKF) is applied to estimate the electrical components connected in the grid, but the covariance matrices need a tedious parameter tuning procedure.

According to the certainty equivalence principle, the overall performance of the grid will be greatly improved provided that the high accuracy and fast converge rate of online physical parameter estimation in the grid can be obtained. Especially, the start-up performance of the inverter can be simplified and the transient response can be improved. In the traditional adaptive parameter estimation algorithm framework such as the gradient descent method, a predictor and/or observer are generally used to generate predictor and/or observer error to design the adaptive law (de Mathelin and Lozano (1999)). However, the utilization of the gradient descent method may suffer from the potential bursting phenomenon, especially when the system is subject to the external disturbances. In order to overcome this issue, several prevalent robust adaptive laws have been successively proposed such as e-modification (Ioannou and Kokotovic (1983)), and σ-modification (Ortega and Tang (1989)). One salient of such robust adaptive law is that a leakage term is established to ensure the boundedness of the estimated parameters. However, the introduced damping term prevents the estimated parameters from converging to their true values, which means that there is a trade-off between accuracy and boundedness. It is worth noting that the online test of persistent excitation (PE) condition which is used to prove the parameter estimation convergence still remains a difficult challenge in the parameter estimation field. Therefore, it is worthy to further investigate a novel adaptive parameter estimation algorithm, which can not only estimate the system parameter accurately but also provide an intuitive approach to verity the PE condition.

Motivated by the above discussions, this study will propose a novel parameter estimation algorithm for the grid-converter system with LCL filter. To realize this purpose, a series of filter operations and auxiliary variables are used to extract the parameter estimation error information, which is used to construct a novel leakage term and online validate the PE condition. Then, a sliding mode term is studied and cooperated with a new leakage term to design the adaptive finite-time parameter estimation algorithm, by which the system parameters can be driven to their true values accurately and fast. The parameter estimation error convergence is rigorously proved in terms of the Lyapunov theory. Finally, simulation results are provided to demonstrate the effectiveness of the proposed method.

This study is organized as follows. **Section 2** provides the dynamic modeling of the grid-connected VSI with LCL filter in continuous-time model. **Section 3** presents the finite-time adaptive estimation algorithm design and analysis, and a comparison to another estimation algorithm. Comparison simulations are given in **Section 4**. Some conclusions are summarized in **Section 5**.

2 Dynamic modeling

In this section, continuous-time model for grid-connected VSI with LCL filter is first described. As shown in **Figure 1**,

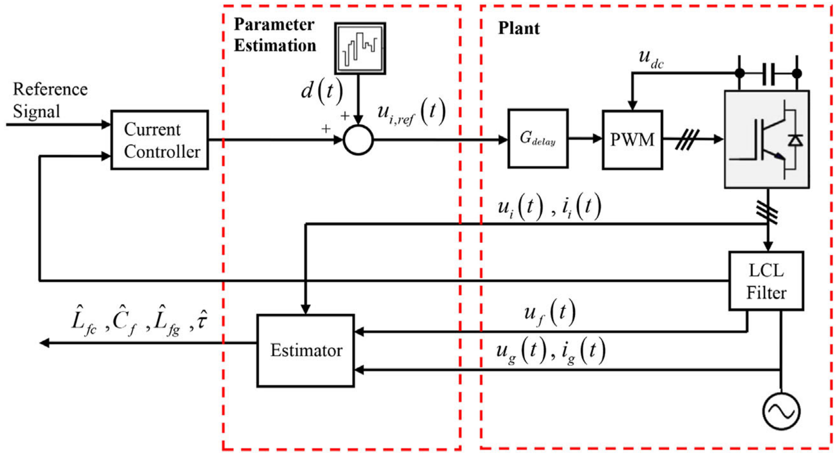

FIGURE 1
Schematic diagram of the estimation setup.

the inverter is supplied with a constant DC voltage $u_{dc}$and an LCL filter is inserted between VSI and the grid to attenuate the switching frequency harmonics caused by VSI. A current controller is applied to regulate the grid-side inductor current and digital control delay G_{delay} of the controller is also considered. Moreover, a parameter estimation scheme is added to the system with external disturbances $d(t)$. Note that the aim of this study is to propose a novel parameter estimation scheme to identify the physical parameters of the LCL filter and the digital control delay of VSI with accuracy and fast converge rate.

2.1 Model of LCL filter

For the ease of subsequent analysis, a single-phase equivalent circuit model of a typical LCL filter is shown in **Figure 2**, which is widely used in the grid application. As shown in **Figure 2**, the symbols u_i and i_i denote the inverter voltage and inverter current. u_f is the voltage across the shunt branch's filter capacitor, u_g and i_g represent the grid-side voltage and grid-side current. L_i, L_g, and C_f represent the inverter side inductance, the grid-side inductance, and the filter capacitance, respectively. Note that in practical engineering applications, the electrical components such as L_i, L_g, and C_f exist uncertainties because of the manufacturing tolerances, temperature changes, and aging phenomenon. Moreover, inductive grid impedance and the leakage inductance caused by the transformer will also lead to the parameter changing of L_i and L_g. In order to estimate the physical parameters of electrical components online, the dynamic of the LCL filter can be given by applying the Krichhoff's law (Massing et al. (2011)), note that equivalent resistors could be ignored since their impedances of them are far less than the one of inductance L_i and L_g.

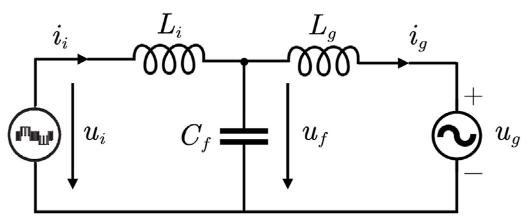

FIGURE 2
Single-phase equivalent circuit diagram.

$$\begin{cases} L_i \dot{i}_i = u_i - u_f \\ C_f \dot{u}_f = i_i - i_g \\ L_g \dot{i}_g = u_f - u_g \end{cases} \tag{1}$$

To facilitate the estimator design, we define the system states as $x_{ig} = \left[i_i, \quad u_f, \quad i_g\right]^T \in \Re^3$, and hence, the state-space form of system (1) can be written as

$$\begin{cases} \dot{x}_{ig} = A_{ig} x_{ig} + B_i u_i + B_g u_g \\ y = C x_{ig} \end{cases} \tag{2}$$

$$A_{ig} = \begin{bmatrix} 0 & -\frac{1}{L_i} & 0 \\ \frac{1}{C_f} & 0 & -\frac{1}{C_f} \\ 0 & \frac{1}{L_g} & 0 \end{bmatrix}, \quad B_i = \begin{bmatrix} \frac{1}{L_i} \\ 0 \\ 0 \end{bmatrix}, \quad B_g = \begin{bmatrix} 0 \\ 0 \\ -\frac{1}{L_g} \end{bmatrix}, \quad C_i = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}, \tag{3}$$

where $A_{ig} \in \mathfrak{R}^{3\times3}$ and $B_i \in \mathfrak{R}^{3\times1}$ and $C_i \in \mathfrak{R}^{1\times3}$ denote the system matrix, input matrix and output matrix, respectively. B_g represents the unknown parameter of the grid-side voltage.

2.2 Model of digitally controlled VSI

The digitally controlled inverters existing time delay includes the computation delay of the microprocessor, sampling period time delay, and time delay of the zero-order hold in the pulse width modulation converter (Agorreta et al. (2010)). Though the three elements are analyzed in the z-domain, few research works focused on the time-domain analysis. In this sense, the following time-continuous model is given:

$$G_{delay} = \frac{e^{-\tau \cdot s} \cdot (1 - e^{-\tau \cdot s})}{\tau \cdot s}, \tag{4}$$

where τ denotes the sampling period.

Note that **Eq. 4** cannot be used to establish the desired state-space form due to its complex transfer function. As analyzed by Agorreta et al. (2010); Houpis (1999); and Houpis and Sheldon (2013), **Eq. 4** can be rewritten in terms of the Pade approximation technique as follows:

$$G_{delay} = \frac{e^{-\tau \cdot s} \cdot (1 - e^{-\tau \cdot s})}{\tau \cdot s} \approx \frac{1}{\tau \cdot s + 1} \cdot \frac{1}{\tau} \cdot \frac{\tau}{0.5\tau \cdot s + 1} \approx \frac{1}{0.5\tau^2 s^2 + 1.5\tau s + 1}. \tag{5}$$

Based on **Eq. 5**, a new G_{delay1} can be obtained:

$$G_{delay1} \approx G_{delay} = \frac{1}{1.5\tau s + 1}. \tag{6}$$

Based on **Eq. 2** and **6**, the comprehensive state-space form of grid-connected VSI with LCL filter can be formulated as follows:

$$\begin{cases} \dot{x} = Ax + B_{uref} u_{i,ref} + B_{ga} u_g + \delta \\ y = Cx \end{cases} \tag{7}$$

where $x = \begin{bmatrix} i_i, & u_f, & i_g, & u_i \end{bmatrix}^T \in \mathfrak{R}^4$ is the overall system state. δ denotes approximation error and measurement noise which can be considered as a bounded disturbance i.e., $\|\delta\| \leqslant \varepsilon_\delta$ for a positive constant $\varepsilon_\delta > 0$.

$$A = \begin{bmatrix} 0 & -\frac{1}{L_i} & 0 & \frac{1}{L_i} \\ \frac{1}{C_f} & 0 & -\frac{1}{C_f} & 0 \\ 0 & \frac{1}{L_g} & 0 & 0 \\ 0 & 0 & 0 & -2/(3\tau) \end{bmatrix}, \quad B_{uref} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 2/(3\tau) \end{bmatrix}, \quad B_{ga} = \begin{bmatrix} 0 \\ 0 \\ -\frac{1}{L_g} \\ 0 \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix}, \tag{8}$$

where $A \in \mathfrak{R}^{4\times4}$ and $C \in \mathfrak{R}^{1\times4}$ denote the augmented system matrix and augmented output matrix. $B_{ref} \in \mathfrak{R}^{4\times1}$ represents the augmented input matrix corresponding with the control input u_{ref} while $B_{ga} \in \mathfrak{R}^{4\times1}$ denotes the unknown parameter of the grid-side voltage u_g. Different from nonparametric frequency-response-based identification, model-based estimation method can describe the power electrical system by modelling with physical laws i.e., Kirchhoff's law. It is not difficult to find out that inductances, capacitances and digital control delay in the grid are directly included in the model **Eq. 7** which paved a new way to estimate these components directly.

ASSUMPTION 1: The system state and the reference control input of the system **Eq. 7** are bounded and accessible for measurement.

Note that Assumption 1 has been widely used in the estimation field [marino1995adaptive, adetola2008finite], and it can be satisfied by applying a proper controller.

3 Online parameter estimation

In this section, we will propose a finite-time adaptive parameter estimation algorithm to online estimate the unknown parameters encountered in the VSI with LCL filter.

3.1 Finite-time adaptive parameter estimation

For the ease of subsequent analysis, **Eq. 7** can be rewritten as

$$\dot{x} = \Phi(x, u)\Theta + \delta, \tag{9}$$

where $\Theta = \begin{bmatrix} 1/L_i, & 1/C_f, & 1/L_g, & -2/(3\tau) \end{bmatrix}^T \in \mathfrak{R}^4$ is the augmented parameter to be estimated and $\Phi(x, u) =$

$\text{diag}\left(-u_f + u_i, \quad i_i - i_g, \quad u_f - u_g, \quad -u_c + u_{ref}\right) \in \mathfrak{R}^{4\times4}$ represents the augmented regressor matrix. To extract the estimation error, a low-pass filter operation is imposed on both sides of **Eq. 9**, and the filtered variables x_f, $\Phi_f\left(x_f, u_f\right)$, δ_f of $x, \Phi(x,u)$ and δ can be defined as:

$$\begin{cases} \kappa\dot{x}_f + x_f = x, x_f(0) = 0 \\ \kappa\dot{\Phi}_f + \Phi_f = \Phi, \Phi_f(0) = 0 \\ \kappa\dot{\delta}_f + \delta_f = \delta, \delta_f(0) = 0 \end{cases} \tag{10}$$

where $\kappa > 0$ is a positive filter parameter. Note that δ_f is only used for analysis.

The motivation for adopting the low-pass filter operation can be divided into two aspects. First, the low-pass filter can significantly eliminate the effect of the high-frequency noises (such as measurement noise), which is contributed to improving parameter estimation performance. Second, the measurement of the derivative terms such as $\dot{i}_i, \dot{u}_f$ and $\dot{i}_g$ is not an easy task, such that the adopted low-pass filter operation can avoid using such derivative.

Substituting **Eq. 10** into **Eq. 9**, one can deduce that

$$\Phi_f\Theta = \dot{x}_f - \delta_f = \frac{x - x_f}{\kappa} - \delta_f. \tag{11}$$

It should be pointed out that the non-zero initial condition $x(0)$ may bring an exponentially decaying term $\frac{1}{\kappa}e^{\frac{-t}{\kappa}}x(0) \to 0$ when $t \to \infty$. Based on this conclusion, the effect of the initial condition will not be considered in the subsequent analysis as (Ortega et al. (2018); Aranovskiy et al. (2016, 2015))

In order to extract the parameter estimation error information with simple algebraic calculation, the auxiliary matrix $P \in \mathfrak{R}^{4\times4}$ and vector $N \in \mathfrak{R}^4$ are first defined as follows:

$$\begin{cases} \dot{P} = -lP + \Phi_f^T\Phi_f, P(0) = 0 \\ \dot{N} = -lN + \Phi_f^T\left[\left(x - x_f\right)/\kappa\right], N(0) = 0 \end{cases} \tag{12}$$

where the parameter $l > 0$ is designed to guarantee the boundness of auxiliary matrix P and vector N. By integrating on both sides of **Eq. 12**, one can deduce that

$$\begin{cases} P(t) = \int_0^t e^{-l(t-r)}\Phi_f^T(r)\Phi_f(r)\,dr \\ N(t) = \int_0^t e^{-l(t-r)}\Phi_f^T(r)\left[\left(x(r) - x_f(r)\right)/k\right]dr \end{cases} \tag{13}$$

Furthermore, another auxiliary vector $H \in \mathfrak{R}^4$ is designed along with **Eq. 7** as

$$H = P\hat{\Theta} - N = -P\tilde{\Theta} + \Psi, \tag{14}$$

where $\hat{\Theta}$ denotes the estimation, i.e., error of unknown system parameters. $\tilde{\Theta} = \Theta - \hat{\Theta}$ is the parameter estimation error. $\Psi = \int_0^t e^{-\ell(t-r)}\phi_f^T(r)\delta_f(r)\mathrm{d}r$ represents the bounded residual error since state x is assumed to be bounded which further means that Φ and Φ_f are also bounded. Hence, the condition $\|\Psi\| \leqslant \delta_\Psi$ is true for a positive constant $\delta_\Psi > 0$. Moreover, we can see that the parameter estimation error information is included in H, which will used to construct a new leakage term to design the adaptive parameter estimation algorithm.

Generally, the persistent excitation (PE) condition is required to guarantee the parameter estimation convergence in the adaptive parameter estimation. To verify the PE condition online, the following Lemma is given.

Lemma 1:

If the regressor matrix Φ defined in **Eq. 9** fulfils the PE condition, the matrix P is positive define, i.e., the minimum eigenvalue of P in **Eq. 12** fulfils the condition $\lambda_{\min}(P) > \sigma > 0$ for a positive constant σ.

Proof: According to the definition of PE (Na et al. (2015)) condition, the inequality $\int_t^{t+T}\Phi_f^T\Phi_f\,dr \geqslant \rho I$ is equivalent to $\int_{t-T}^t \Phi_f^T\Phi_f\,dr \geqslant \rho I$ for $t > T > 0$. Therefore, one can deduce that the inequality $\int_{t-T}^t \Phi_f^T\Phi_f\,dr \geqslant \rho I$ is true for $t > T > 0$ provided that the filtered regressor matrix Φ_f satisfies the PE condition. Note that the Φ_f is the filtered variable of Φ, such that the PE condition for Φ is equivalent for Φ_f. Therefore, considering the integrating interval $\lambda \in [t - T, t]$, the inequality $e^{-l(t-\lambda)} \geqslant e^{-lT} > 0$ is true for $t - \lambda < T$, one can deduce that

$$\int_{t-T}^t e^{-l(t-\lambda)}\Phi_f^T\Phi_f\,d\lambda \geqslant \int_{t-T}^t e^{-lT}\Phi_f^T\Phi_f\,d\lambda \geqslant e^{-lT}\rho I. \tag{15}$$

For $t > T > 0$, **Eq. 15** can be rewritten as

$$\int_0^t e^{-l(t-\lambda)}\Phi_f^T\Phi_f\,d\lambda > \int_{t-T}^t e^{-l(t-\lambda)}\Phi_f^T\Phi_f\,d\lambda. \tag{16}$$

Based on **Eq. 15** and **16**, we can obtain

$$P = \int_0^t e^{-l(t-\lambda)}\Phi_f^T\Phi_f\,d\lambda > e^{-lT}\int_{t-T}^t \Phi_f^T\Phi_f\,d\lambda \geqslant e^{-lT}\rho I. \tag{17}$$

According to **Eq. 17**, we can claim that if the matrix P is positive definite, the condition $\lambda_{\min}(P) > \sigma > 0$ is true for $\sigma = e^{-lT}\rho$.

Remark 1: In order to increase the excitation level, an excitation signal in $\alpha\beta$ frame is added to the output of the current loop controller which is also the reference input voltage of inverter u_{ref}. The excitation signal is given as $u_n = u_{n\alpha} + ju_{n\beta}$. We add the excitation signal in β-direction since it can reduce the effects of the inverter nonlinearities on the PWM generator and parameter estimation (Koppinen et al. (2017)). Moreover, the trade-off between excitation power and current harmonic distortion should be carefully considered since a small amplitude of excitation signal will not excite the desired frequency components, while a larger one will cause harmonic distortion in the grid current.

Given the fact that the utilization of parameter estimation error $P\tilde{\Theta}$ in adaptation will be beneficial for the parameter estimation performance, a finite-time adaptive parameter estimation scheme is developed as follows:

$$\dot{\hat{\Theta}} = -\Gamma_1\frac{P^T H}{\|H\|}, \tag{18}$$

where $\Gamma_1 > 0, \Gamma_1 \in \mathfrak{R}^{4\times4}$.

Theorem 1:

For inverter system with LCL filter **Eq. 9** and the parameter adaptation law in **Eq. 18**, the estimation parameter $\hat{\Theta}$ is bounded and the estimation error $\tilde{\Theta}$ will converge to a small set around zero i.e., $\tilde{\Theta}$ is uniformly ultimately bounded (UUB) in a finite time satisfying $\lim_{t\to\infty} P_1\tilde{\theta} = \Psi$.

Proof:

In the inverter system equipped by LCL filter with extra excitation signal, we assume that Φ fulfils the PE condition. And based on Lemma 1, we can guarantee that $\lambda_{\min}(P) > \sigma > 0$. Then, we first proof that the estimation parameter $\hat{\Theta}$ is bounded. By calculating the time derivative of $P^{-1}H = -\tilde{\Theta} + P^{-1}\Psi$, one can get

$$\frac{\partial P^{-1}H}{\partial t} = -\dot{\tilde{\Theta}} + \frac{\partial P^{-1}}{\partial t}\Psi + P^{-1}\dot{\Psi} = \dot{\hat{\Theta}} - P^{-1}\dot{P}P^{-1}\Psi + P^{-1}\dot{\Psi} = \dot{\hat{\Theta}} + \Psi', \tag{19}$$

where $\Psi' = -P^{-1}\dot{P}P^{-1}\Psi + P^{-1}\dot{\Psi}$; we then choose the Lyapunov function as $V = 1/2H^TP^{-1}P^{-1}H$, and its derivation can be deduced as

$$\dot{V} = H^TP^{-1}\frac{\partial P^{-1}H}{\partial t} = -H^TP^{-1}\Gamma_1\frac{P^TH}{\|H\|} + H^TP^{-1}\Psi' \leqslant -\left(\lambda_{\min}(\Gamma_1) - \|P^{-1}\Psi'\|\right)\|H\|. \tag{20}$$

Focusing on the term $\|P^{-1}\Psi'\|$, one can find that Ψ and $\dot{\Psi}$ is bounded since the disturbance δ and filtered residual error Ψ_f are bounded, P and P^{-1} are also bounded for bounded Ψ_f. Furthermore, PE condition can further ensure that P^{-1} is bounded. Hence, if Γ_1 is large enough to satisfy $\lambda_{\min}(\Gamma_1) > \|P^{-1}\Psi'\|$, the estimation error $\tilde{\Theta}$ and estimation parameter are all bounded.

According to **Eq. 20** and rewrite it as $\dot{V} \leqslant -\mu\sqrt{V}$ with $\mu = \sqrt{2}\sigma\left(\lambda_{\min}(\Gamma_1) - \|P^{-1}\Psi'\|\right)$ which is a positive scalar and needs to be selected large enough. From finite-time convergence of Lyapunov solution V, that the auxiliary vector with parameter error will converge to zero in finite time, i.e., $\lim_{t\to\infty}H = 0$ in $t_f = 2\sqrt{V(0)}/\mu$. Based on $\dot{V} \leqslant -\mu\sqrt{V}$ we can claim that in $t \in [0, t_f]$, the plant **Eq. 18** evolves in a sliding mode along the surface $H = 0$, which further means that $\lim_{t\to\infty}P\tilde{\Theta} = \Psi$ is true in finite time. It should be noted that the sliding mode term in **Eq. 18** will not lead to severe chattering problem in the estimated parameters as the integrating operation imposed on term $H/\|H\|$ (Na et al. (2019)).

Remark 2:

From the above proof, one can find that the convergence rate of estimation error depends on the learning gain Γ_1 and excitation level σ. Generally, a large learning gain and excitation level can obtain a faster converge rate, while too large gain may trigger parameter oscillation. The forgetting factor l in **Eq. 12** is set to the penalty of the initial condition which is not suggested to be large. Filter parameter κ in **Eq. 10** denotes the "bandwidth" of the filter. Hence, there is also a trade-off between converge rate and robustness in selecting the value of the forgetting factor and filter parameter.

3.2 Gradient-based adaptive parameter estimation

In order to further show the superiority of the proposed adaptive law over conventional method, a brief discussion of gradient-based adaptive parameter estimation algorithm is provided in this subsection. First, an observer is designed for the system in **Eq. 7**:

$$\dot{\hat{x}} = \Phi(x,u)\hat{\alpha} + \lambda(x - \hat{x}), \tag{21}$$

where $\lambda > 0$ denotes the observer gain, $\Phi(x,u) = \mathrm{diag}\left(-u_f + u_i,\quad i_i - i_g,\quad u_f - u_g,\quad -u_c + u_{ref}\right) \in \Re^{4\times4}$ denotes the regressor matrix and $\hat{\alpha} = \left[1/\hat{L}_i,\quad 1/\hat{C}_f,\quad 1/\hat{L}_g,\quad -2/(3\hat{\tau})\right]^T \in \Re^4$ represents the unknown parameter. $\hat{x} = \left[\hat{i}_i,\quad \hat{u}_f,\quad \hat{i}_g,\quad \hat{u}_i\right]^T \in \Re^4$ is the observer state which is needed to be observed. First, we design the observer error $e = x - \hat{x}$, $e \in \Re^4$ and the corresponding time derivative can be calculated as

$$\dot{e} = -\lambda e + \Phi(x,u)\tilde{\alpha}. \tag{22}$$

In order to minimize the power of the estimation error e by $\partial e^2/\partial\alpha = 0$, one can design the adaptive law by using the observer error e as

$$\dot{\hat{\alpha}} = \Gamma_2\Phi^T\frac{e}{m^2}, \tag{23}$$

where Γ_2 denotes the learning gain of gradient-based adaptive law, m^2 is a normalizing signal designed by $m = 1 + \|\Phi\|$ as explained by de Mathelin and Lozano (1999). According to **Eq. 23**, we can find that different from the finite-time estimation algorithm **Eq. 18** with parameter estimation error, the gradient-based method depends on a predictor/observer to create the predictor/observer error for driving the adaptive law which may indirect for online parameter estimation.

Remark 3: Grid converters are usually controlled by model-based control algorithms, which means that the estimated parameters like the LCL filter will participate directly/indirectly in the design of the controller. Moreover, from (Xie and Chen (2021); Tao et al. (2022)) we can find that the accuracy and the converge rate of the estimated parameter can impact the overall control performance, which further suggests that a proper estimation algorithm dedicates to grid-connected control. Though there exist some online parameter estimation methods such as gradient-based adaptive law and σ-modification, the estimated parameters may need a fairly time to converge or even not able to converge to the real value. On the contrary, the proposed finite-time adaptive estimation algorithm can drive the estimated parameters toward the real value in finite time. In this sense, the overall control performance can be improved, the controller's overall performance, especially during the start-up period.

4 Simulation

In this section, the parameter estimation of the LCL filter with VSI is simulated in MATLAB/SimPowerSystems software environment. Comparative simulation results are given to demonstrate the effectiveness of the proposed method. The parameters to be estimated and the associate parameters are listed in Table 1 (Koppinen et al. (2017)). Note that the DC voltage is constant and the time delay of digitally control in VSI is considered. Moreover, the sampling frequency is set as $f_s = 10\text{kHz}$ and the inverter switching frequency is set at half of the sampling frequency i.e., $f_{PWM} = 5\text{kHz}$.

The current controller implemented in this simulation is a typical PI controller based on dq synchronous reference frame and the purpose of the controller is to regulate the grid-side inductor current i_q. Note that some existing PWM-based control strategies such as repetitive controllers (De Almeida et al. (2014)) and resonant integrator controllers (Yepes et al. (2010)) can be used instead. Moreover, the up-to-date grid-voltage angle ω_g can be calculated from the measured grid voltage by the phase-locked loop (PLL) method.

Comparison to gradient-based algorithms: For a fair comparison, the control parameters in the current controller and PLL are taken as the same value, which means that the input signal u_{ref} is the same in two estimation process. Moreover, an extra noise $d = 10rand(0.1)$ with mean 0 and variance 0.1 is added into the system to increase the excitation level.

From Figure 3, it can be found that the minimum eigenvalue of matrix $P(t)$ is larger than zero (e.g., $\lambda_{\min}(P(t)) > \sigma > 0$). Therefore, the regressor vector Φ satisfies the PE condition according to Lemma 1. Moreover, by calculating the $\lambda_{\min}(P(t))$, we can online validate the PE condition, which is helpful in practical application. Note that in finite-time estimation, as one can find in previous proof of the theorem, input signals with high excitation levels may improve the convergence rate of estimation errors.

The associated parameters are chosen as $\Gamma_1 = 5\text{diag}\left(50, 5\times10^6, 5, 1\right)$, filter constant $\kappa = 0.01$ and forgetting factor $l = 0.2$ via a trial-and-error method. Note that the initial values in the simulation are set as zero. And the parameters in gradient-based parameter estimation Eq. 23 are set as $\Gamma_2 = 5\text{diag}\left(400, 5\times10^6, 6, 1\right)$ and $\lambda = 5\text{diag}\left(30, 5\times10^3, 50, 20\right)$.

Figure 4 illustrates the comparative parameter estimation performance between the proposed adaptive estimation algorithm and gradient-based estimation algorithm. The estimated parameters based on the aforementioned algorithms are listed in Table 2. As shown in Figure 4 and Table 2, we can find that the proposed adaptive estimation algorithm Eq. 18 obtains a fast parameter convergence speed and accuracy than that of the gradient-based algorithm. The reason for this phenomenon is that the information of parameter estimation error $P\tilde{\Theta}$ in H is used to drive the adaptive law Eq. 18, while only the observer error e is employed in the gradient-based algorithm, and it can again verify the effectiveness of the proposed algorithm.

Figure 5 provides the frequency responses of the proposed adaptive law and gradient-based adaptive law in terms of the Bode diagram, respectively. We can find from Figure 5 that the proposed adaptive law can accurately estimate the resonant peak and slopes at the high frequency of the LCL filter in the presence of time delay compared with the gradient-based adaptive law due to the precise parameter estimation performance. The improved performance can be also found from the phase angle. Based on the above simulation results, we can further deduce that the proposed parameter estimation method for the LCL filter may provide an alternative way to carry out the corresponding controller design to attenuate the resonant peak to obtain a stable grid current.

TABLE 1 Simulation system parameters.

Symbol	Value	Symbol	Value
u_{dc}	800 V	L_i	3.3 mH
u_g	$400\sqrt{2/3}$ V	C_f	8.8 μF
ω_g	$2\pi\cdot 50$ rad/s	L_g	3.0 mH
f_s	10 kHz	f_{PWM}	5 kHz

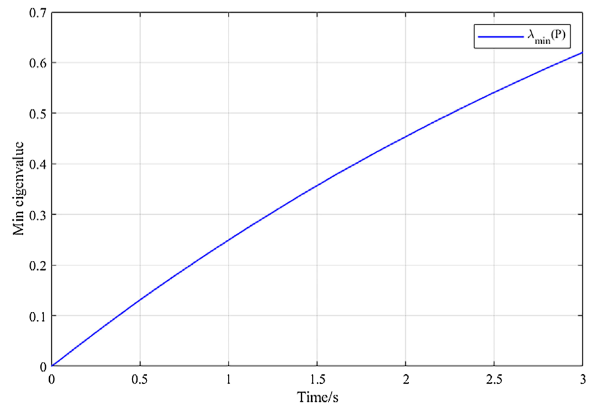

FIGURE 3
Minimum eigenvalue of $P(t)$.

TABLE 2 Estimation of parameters.

Symbol	Reference value	Finite time	Gradient based
$1/L_i$	303.03	302.14	334.33
$1/C_f$	113636.36	113510.83	94854.50
$1/L_g$	333.33	332.46	340.10
$1/\tau$	10000.00	9920.66	10288.59

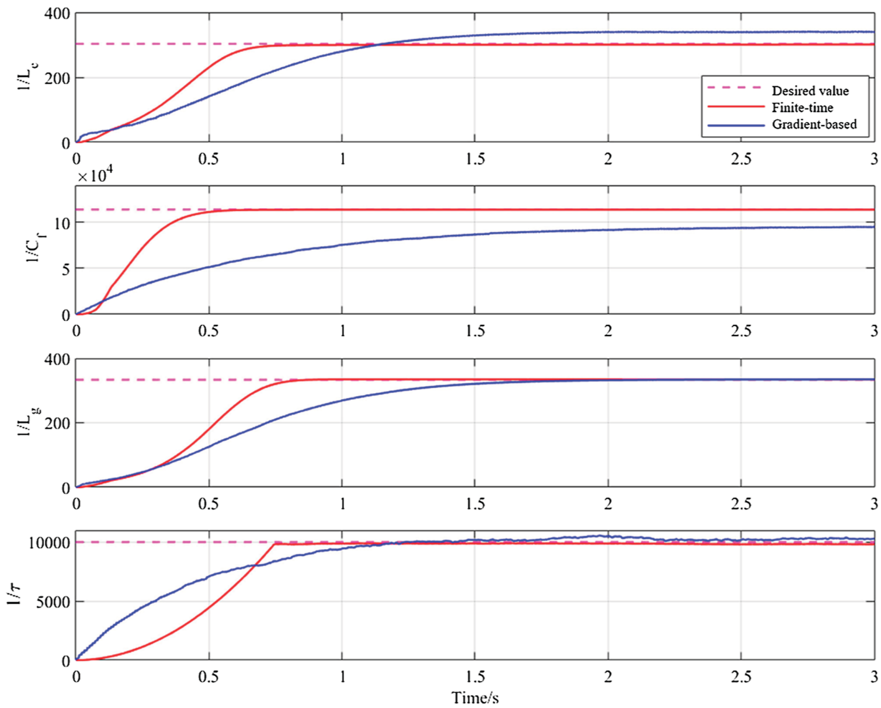

FIGURE 4
Parameter estimation compared with the proposed method and gradient-based method.

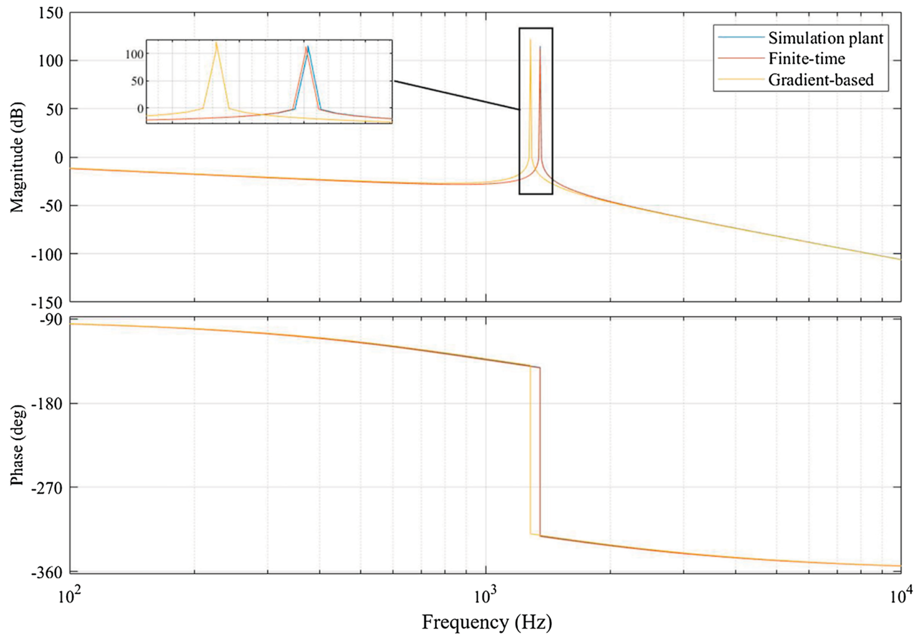

FIGURE 5
Frequency responses of LCL filter with two estimation methods.

5 Conclusion

In this study, an online finite-time adaptive parameter estimation method was proposed for a grid-converter system with LCL filter in time-continuous state-space form. Different from the conventional predictor/observer-based method, the proposed framework could achieve high accuracy and fast converge rate by applying parameter estimation error in driving adaptive law and a sliding mode term is studied and cooperated with new leakage term to design the finite-time adaptive parameter estimation algorithm. Theoretical analysis was studied by Lyapunov theory to demonstrate the convergence of the estimation error. Moreover, a comparative simulation was developed to illustrate the effectiveness of the proposed method. Applying the proposed method to estimate the electrical components can be beneficial for fault diagnosis of the electrical power system. The future work will focus on combining the proposed parameter estimation method with a certain controller to enhance the overall control performance of the grid, and experiments will also carry out in the future.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

Author contributions

XX: analysis, modeling, and writing—original draft. ZS: data curation and writing—original draft. XW: conceptualization and methodology. CX: writing—reviewing the draft. SL: writing—reviewing and editing.

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Conflict of interest

XX, CX, and SL were employed by the Electric Power Research Institute of Yunnan Power Grid Co., Ltd.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

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