

Article

Frequency Control Capability Estimation for Renewable Energy Stations Accounting for Dynamic Response Variations and Power Decoupling

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Abstract

The large-scale integration of converter-interfaced renewable energy sources has significantly reduced power system inertia, posing challenges to frequency stability. Although virtual inertia and primary frequency control can enhance the frequency support capability of renewable energy units, their actual performance often deviates from set values due to dynamic response differences among various energy sources (e.g., energy storage, photovoltaic, and wind power) and coupling between inertia and primary regulation power. Existing evaluation methods fail to accurately decouple these components or account for unit-specific dynamic characteristics, leading to considerable estimation errors. To address these issues, this paper proposes a novel estimation method for the frequency regulation capability of renewable energy stations. First, the dynamic frequency response characteristics of synchronous and renewable generators are compared. Then, a decoupling method is developed to separate virtual inertia power from primary frequency regulation power by leveraging their distinct response features. A first-order plus delay time (FOPDT) model is employed to characterize the external frequency response of different renewable energy units. The primary frequency regulation coefficient is estimated using a sliding window integration method, and the virtual inertia time constant is identified via a gradient descent algorithm based on the decoupled inertia power. A hardware-in-the-loop experimental platform is constructed using a real-time digital simulator (RTDS) and phasor measurement units (PMUs) to validate the proposed method. Simulation results show that the estimation errors for energy storage, photovoltaic, and wind power units are 0.63%, 6.38%, and 8.38% for the virtual inertia time constant and 0.45%, 0.72%, and 3.81% for the primary frequency regulation coefficient, respectively. Field test data further confirm the practical applicability and accuracy of the approach. The proposed method enables precise frequency control capability estimation, providing a reliable basis for parameter setting and capacity configuration of frequency regulation resources in low-inertia power systems.

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Keywords: renewable energy resources; frequency support capability estimation; virtual inertia; primary frequency control; frequency stability

1. Introduction

To deal with the intensifying global energy challenges and environmental crises, China has established its “carbon peaking and carbon neutrality” goals [1], where large-scale renewable energy deployment plays a pivotal role. However, as wind and solar power grids expand, the power system’s inertia and primary frequency regulation capabilities have been declining, leading to deteriorating frequency stability after disturbances [2]. Given the limited capacity of traditional frequency regulation resources, renewable energy plants become crucial for suppressing frequency deviations and maintaining grid stability. International grid interconnection guidelines mandate that renewable facilities must participate in grid frequency support [3,4].

To meet these requirements, renewable energy plants typically employ control strategies that emulate the response of synchronous generators, thereby providing active power in proportion to frequency deviations and rate of change in frequency. Control methods are categorized into two types: grid-following control (GFL) and grid-forming control (GFM) [5,6]. Due to the risk of instability in GFM during multi-unit operation scenarios [7], only single-unit pilot retrofits have been implemented at the engineering application level, with no large-scale station-level applications yet [8]. In contrast, the simple control mechanism and easy retrofitting features significantly reduce the construction costs of GFL, making it widely adopted in practical projects. Most virtual inertia and primary frequency regulation functions in China’s newly grid-connected renewable energy stations are currently achieved through this method [9].

Despite the widespread adoption of GFL, several technical challenges remain. As the frequency modulation capacity of new energy stations depends on wind and solar resources and reserves, when the frequency modulation resources are limited, the frequency support capacity of new energy stations to the power grid may not reach the set value, and the frequency modulation of new energy stations faces the problem of not moving when adjusted and not reaching the target [10,11]. Therefore, accurate assessment of renewable energy stations’ frequency regulation capabilities helps verify compliance with national standards and ensures stable system operation. Additionally, due to the small single-unit capacity of wind and solar power, large-scale support effectiveness relies on multi-unit integration. With numerous frequency regulation control targets at renewable energy stations, control parameters typically require optimization based on operational conditions [12–14]. Consequently, precise evaluation of the frequency regulation capabilities for these stations validates the rationality of their frequency control strategies and provides a foundation for optimizing station-level frequency management [15].

Existing research has primarily focused on characterizing the frequency regulation response of renewable energy stations using analogies to the rotor motion equations of synchronous generators. These studies employ equivalent inertia, time constants, and equivalent frequency modulation coefficients to evaluate the inertia and primary FM capabilities of renewable energy power stations. References [16–18] utilize frequency response models to calculate primary FM coefficients by analyzing the ratio between post-disturbance steady-state active power variations and frequency deviations, while deriving equivalent inertia time constants through the fastest descent optimization algorithm based on power-frequency rate relationships. Reference [19] derives primary FM coefficients and inertia time constants using covariance matrices from PMU measurements and least squares methods. To reduce dependence on system disturbance randomness, reference [20] establishes approximate relationships between system impedance and frequency response transfer functions through small disturbance injections, enabling estimation of FM coefficients and inertia.

However, existing evaluation methods face challenges due to data quality limitations and model uncertainties. Critical factors contributing to errors include FM control delays,

response hysteresis, and coupling effects between FM and inertia responses, which are particularly significant for inertia time constant estimation. These issues are particularly pronounced in the estimation of inertia time constants. While references [21–23] enhanced FM capability assessments by accounting for system response delays, their methodologies only considered rapidly responsive renewable units like supercapacitors or electrochemical energy storage systems, lacking validation for slower-responsive renewables such as wind and solar power. Furthermore, while reference [21] considered the coupling effect of primary frequency regulation power when evaluating virtual inertia time constants, it failed to specifically analyze the dynamic response process of new energy units during primary frequency regulation. This oversight may lead to inaccurate decoupling between inertia response and power output, thereby affecting the accuracy of evaluation results.

To address these issues and improve assessment precision, this paper proposes a novel evaluation method for new energy station frequency regulation capabilities that incorporates frequency regulation control delays, dynamic response differences in new energy units, and the coupling effects between primary frequency regulation and inertia response. The frequency regulation mechanisms and delay characteristics of new energy auxiliary controls were introduced first. And then a sliding average window integration method to evaluate primary frequency regulation adjustment coefficients was employed based on the characteristic differences between primary frequency regulation and virtual inertia output power. A response external characteristic model based on a first-order plus delay time (FOPDT) component was then constructed to decouple primary frequency regulation from virtual inertia regulation power. Using the gradient descent algorithm, the virtual inertia time constant was identified. Finally, a hardware-in-the-loop experimental platform built with a Real-Time Digital Simulation System (RTDS) was utilized to validate the proposed method's correctness and evaluation accuracy. Field test data from a specific power station further confirmed the practicality and reliability of the proposed approach. This methodology enables frequency regulation capability evaluation during functional testing phases at power stations and meets real-time assessment requirements after formal commissioning.

The remainder of this paper is organized as follows. Section 2 analyzes the frequency regulation control strategies and dynamic response characteristics of renewable energy stations. Section 3 presents the proposed evaluation method for primary frequency regulation coefficients and virtual inertia time constants. Section 4 describes the hardware-in-the-loop experimental platform and validates the proposed method through simulation case studies. Section 5 further verifies the method using field test data. Finally, Section 6 concludes the paper.

Research Gap: Existing frequency regulation capability evaluation methods for renewable energy stations overlook the dynamic response differences among various renewable units (e.g., energy storage, photovoltaic, and wind power) and fail to properly decouple virtual inertia power from primary frequency regulation power. This leads to significant estimation errors, particularly for slower-responding units.

Motivation: To improve evaluation accuracy, this work proposes a method that accounts for dynamic response variations, decouples inertia and primary regulation power, and incorporates realistic control delays using an FOPDT model. The proposed approach provides more reliable estimates of virtual inertia time constants and primary frequency regulation coefficients, supporting better parameter optimization and grid stability management.

The main novelties and contributions of this work are summarized as follows:

Novel decoupling method for frequency regulation power: Unlike existing approaches that treat virtual inertia and primary frequency regulation power as a combined entity, we propose a decoupling method that separates these two components by leverag-

ing the characteristic differences in their response processes. This enables more accurate extraction of virtual inertia power, which is essential for precise inertia time constant estimation.

Explicit consideration of dynamic response differences among renewable units: While most existing methods assume uniform response characteristics across different renewable energy units, our approach explicitly accounts for the significant variations in ramp rates and response delays among energy storage, photovoltaic, and wind power systems. This is achieved through a first-order plus delay time (FOPDT) model that quantitatively characterizes the external frequency response of each unit type.

Unified evaluation framework applicable to multiple renewable energy sources: Previous studies have primarily focused on fast-responding units such as energy storage, with limited validation for slower-responding wind and photovoltaic systems. Our proposed method provides a unified framework that enables accurate estimation of both the primary frequency regulation coefficient and virtual inertia time constant across different types of renewable energy stations, as validated through hardware-in-the-loop experiments and field data.

2. Analysis of New Energy Frequency Modulation Control Strategy and Frequency Modulation Characteristics

As shown in Figure 1, the schematic diagram of the typical frequency dynamic of the system after the power system encounters a frequency disturbance is displayed. It can be divided into the inertia response stage, the first frequency modulation response stage, and the second frequency modulation response stage and finally recover to the rated frequency [24].

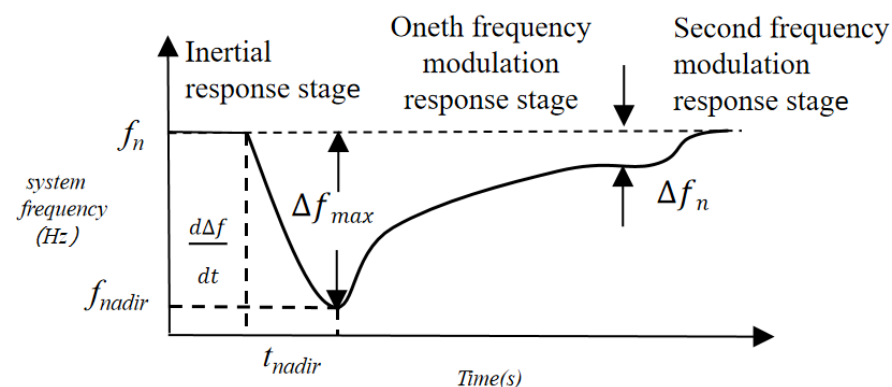


Figure 1. Frequency response curve.

Where t_{nadir} denotes the time instant when the frequency reaches its minimum value after a disturbance.

The dynamic frequency response of power systems is typically modeled using rotor motion equations [25]:

$$2H \frac{d\Delta f}{dt} + D\Delta f = \Delta P_m - \Delta P_e \quad (1)$$

where H represents the system's equivalent inertia time constant; D denotes the equivalent reactance; Δf indicates the frequency deviation; ΔP_m signifies the mechanical power variation; and ΔP_e corresponds to the electromagnetic power fluctuation.

For a synchronous machine, after the load disturbance occurs, the electromagnetic power and mechanical power are unbalanced. The instantaneous action of inertia response converts the kinetic energy stored in the rotor into inertia support power, releasing or absorbing energy to the system to suppress the rapid frequency change. When the fre-

quency changes beyond the dead zone, the system governor acts to adjust the input mechanical power to change the output power of the generator. The primary frequency modulation and the inertia response work together to balance the electromagnetic power and gradually restore the system frequency to stability. The essence of synchronous generator frequency modulation is to continuously change the air intake or water intake to adjust the output power through frequency deviation. The adjustment response has a delay, and the adjustment time of thermal power units is generally not more than 45 s, and that of hydroelectric units is not more than 30 s [3].

New energy systems incorporate analog synchronous generator rotor motion equations into controllers, enabling them to exhibit inertia and primary frequency regulation characteristics similar to synchronous generators. In current engineering practice, GFL is predominantly adopted, typically comprising two components: virtual inertia control and droop control. The transfer function of GFL control is expressed as:

$$G_{GFL}(s) = -\frac{\Delta P_{REU}(s)}{\Delta f(s)} = H_{REU}s + K_{REU} \quad (2)$$

In the formula: P_{REU} represents the active power of new energy stations measured by PMU; H_{REU} and K_{REU} denote the virtual inertia time constant and primary frequency regulation coefficient, respectively. The virtual inertia control of renewable energy differs fundamentally from synchronous generation and unit inertia response. When load disturbances occur, causing system frequency fluctuations, the control loop generates power control signals through virtual inertia and primary frequency regulation to adjust output power and maintain a stable system frequency. Although renewable energy's primary frequency regulation demonstrates faster power response speed than synchronous generators [26], the inertia response cannot achieve instantaneous action due to inherent delays. The inherent delay in GFL signal transmission includes frequency measurement and communication links, which can reach hundreds of milliseconds [27]. Additionally, the power response of new energy units is not instantaneous, but there is a climbing time, which makes the output power of new energy stations vary according to different response units. The composition of delays is illustrated in Figure 2.

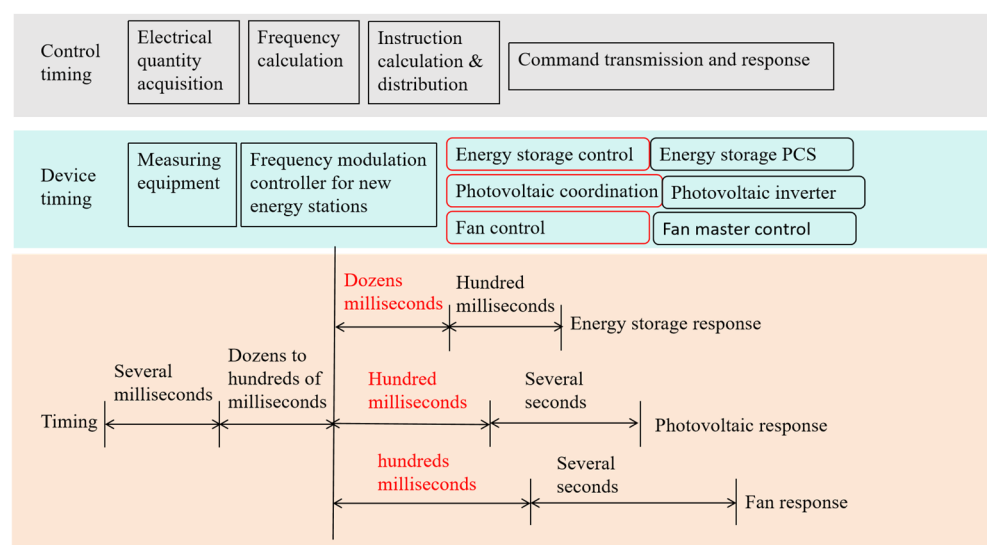


Figure 2. Composition of the response delay of REU.

The complete frequency response model of the renewable energy station, from frequency deviation input to active power output, can be expressed as a cascade of three key components: the frequency measurement and control delay, the GFL strategy, and the dynamic response of the renewable energy unit. The overall transfer function is given by:

$$G_{total}(s) = \frac{\Delta P_{REU}(s)}{\Delta f(s)} = \frac{e^{-\tau s}}{\text{Control delay}} \cdot \frac{(H_{REU}s + K_{REU})}{\text{GFL control}} \cdot \frac{1}{\text{Unit dynamic response}} \quad (3)$$

where $G_{total}(s)$ represents the total control delay, including frequency measurement delay, communication delay, and computational delay; $H_{REU}s$ is the virtual inertia time constant of the renewable energy station; K_{REU} is the primary frequency regulation coefficient; $T_{REU}s$ is the equivalent response time constant of the renewable energy unit, characterizing the power ramp rate of the specific unit type (energy storage, photovoltaic, or wind power).

We now explicitly discuss that control delays, while necessary to model for accurate capability estimation, also have implications for system stability. We cite key references showing that delays introduce phase lag and can reduce stability margins and that delay-dependent stability analysis is an active research area.

This complete transfer function model integrates the three main factors that influence frequency regulation capability: (i) control delays, (ii) virtual inertia and primary frequency regulation control strategies, and (iii) the dynamic response characteristics of different renewable energy units. The model serves as the foundation for the proposed decoupling method and parameter identification approach.

In MATLAB/Simulink (version R2021a), a system frequency response model (SFR) was constructed to further analyze the frequency response characteristics of different power sources. Using the GFL method mentioned earlier, the dynamic response times for energy storage, photovoltaic, and wind power were set according to the national standard requirements, with reference ranges of 0.1 s, 1.25 s, and 2.25 s, respectively [3]. Meanwhile, a 5% load disturbance was introduced to the system. Due to varying power response times among renewable energy units, significant differences exist in their inertia and primary frequency regulation responses. Therefore, accurately assessing the frequency regulation capability of renewable energy stations requires considering the response variations among different frequency regulation units.

It is important to clarify why photovoltaic (PV) power stations exhibit relatively slow system-level response times despite the inherently fast physical response of PV cells themselves (millisecond-level). This apparent paradox is explained by three key factors. First, utility-scale PV stations adopt a centralized control architecture with thousands of distributed inverters. The frequency regulation process involves multiple stages: frequency detection by the central controller, command calculation, communication network transmission, and command execution by each inverter. These multi-level communication and control delays, including sensor sampling, controller computation, and network latency, constitute the dominant component of the total response time. Field measurements have confirmed that communication delays between the central controller and generation units significantly affect primary frequency regulation performance. Second, while inverter power electronic switching operates at the millisecond level, the speed-limiting factor is the maximum power point tracking (MPPT) algorithm. To participate in frequency regulation, inverters must transition from MPPT mode to active power reserve mode—a process that itself requires time. Research indicates that the dominant factor limiting PV frequency response speed is the second-level power tracking algorithm, not the millisecond-level response of PV modules or voltage/current control loops. Conventional inverter MPPT algorithms exhibit notably slow power execution response speeds, with MPPT algorithm response delays potentially exceeding 100 ms. Third, PV stations typically operate at the MPPT point where output is maximized, thus they cannot provide upward regulation without curtailing generation to reserve adjustable capacity. This operational strategy adjustment adds further complexity and time to the system response. In contrast, energy storage systems respond much faster due to simpler architecture, more direct con-

trol, and no reserve capacity constraint. Therefore, the classification of PV as “slow” in this paper refers to system-level engineering response time, not the physical response of PV cells themselves.

3. Evaluation Method of New Energy Frequency Modulation Capacity

The proposed evaluation method for new energy frequency regulation capability in this paper proceeds through the following steps:

- (1) Selecting and preprocessing input data required for frequency regulation capability assessment;
- (2) Analyzing the active power response characteristics of virtual inertia and primary frequency regulation, and evaluating the primary frequency regulation coefficient using a sliding average window;
- (3) Considering the response time of new energy frequency regulation control, decouple primary frequency regulation power and virtual inertia frequency regulation power based on a discretized frequency-power algorithm;
- (4) Estimating the virtual inertia time constant using the gradient descent algorithm, where the input data include: (a) the decoupled virtual inertia power $\Delta P_{v,i}(t)$ obtained from Equation (11), (b) the frequency deviation $\Delta f(t)$ measured by PMU, and (c) the frequency change rate $\frac{df(t)}{dt}$ derived from the frequency measurements.

3.1. Data Selection and Processing for New Energy Frequency Regulation Capability Assessment

To accurately reflect the actual frequency regulation capability of renewable energy power stations, this study employs active power, frequency, and frequency variation rate data measured by PMUs at grid-connected points after triggering frequency stabilization control when frequency fluctuations exceed the dead zone. The moment t_0 when the frequency regulation dead zone is crossed is determined based on the frequency data. To calculate the frequency regulation power increment, the active power operating point before the renewable energy station participated in frequency regulation is calculated as the normal operation reference power P_0 . Considering the fluctuation characteristics of renewable energy output and the time scale of frequency regulation actions, the average active power data within one second before t_0 is used to calculate P_0 , thereby reducing errors caused by power fluctuations and potential noise in the measurement data.

$$P_0 = \frac{\sum_{i=0}^{1/T_s} P_{REU}(t_0 - iT_s)}{1/T_s} \quad (4)$$

where t_0 is the moment when the FM dead zone is crossed; T_s is the sampling time interval of PMU, 20 ms.

3.2. Evaluation of the Primary Frequency Regulation Coefficient for New Energy

In typical GFL systems, the dead zone for primary frequency regulation at renewable energy stations [3] and virtual inertia control dead zone [4] are set to ± 0.05 Hz. During frequency disturbance events, these stations simultaneously adjust power output based on both frequency rate changes and frequency deviations. This coupling between new energy sources, virtual inertia, and primary frequency regulation results in measured active power data that includes both virtual inertia-based frequency regulation generation and primary frequency regulation generation. However, directly assessing the virtual inertia time constant and primary frequency regulation coefficient remains challenging. To address this, the primary frequency regulation coefficient by analyzing their response process differences was first evaluated in this section. Subsequently, decoupling primary frequency regulation power from virtual inertia frequency regulation power is achieved through dynamic power adjustment characteristics, enabling accurate assessment of the

virtual inertia time constant. According to the control principles of GFL, during the initial disturbance phase, both virtual inertia power and primary frequency regulation power are active. In the later disturbance phase, when frequency stabilizes, the virtual inertia generation power approaches zero. Consequently, steady-state frequency regulation power is primarily supplied by primary frequency regulation control. Additionally, the rapid power regulation capability of power electronic devices ensures complete station response during steady states. The alignment between output power/frequency deviation and primary frequency regulation models enhances the accuracy of regulation coefficient evaluation.

In conclusion, to further reduce the errors caused by power fluctuations and potential noise in the measurement data, it is considered to carry out a rolling evaluation of the tuning coefficients based on the sliding average window integration method from the perspective of energy, according to the relationship formula of one frequency modulation control.

$$\Delta P_{(t)} = -K_{REU}(f(t) - f_0 - f_{db}) \quad (5)$$

where ΔP represents the total additional generation power measured by the PMU at the new energy station's grid-connected point; f_0 denotes the system's reference frequency of 50 Hz; and f_{db} indicates the frequency regulation deadband, defined as 0.033 Hz~0.05 Hz [2] according to current standards. By integrating both sides of the equation, the evaluation method for primary frequency regulation coefficients can be derived:

$$K_{REU}(t_n) \approx \frac{\int_{t_n}^{t_n+t_w} \Delta P(t) dt}{-\int_{t_n}^{t_n+t_w} (f(t) - f_0 - f_{db}) dt} \quad (6)$$

where t_w represents the window length of the moving average evaluation method; $K_{REU}(t_n)$ denotes the evaluation value of the frequency modulation coefficient at the n -th sampling point. The evaluation result is output by taking the mean of all evaluation results within each window:

$$K_{REU_adv}(t_n) = \frac{\sum_{i=0}^{t_w} K_{REU}(t_n+i)}{t_w} \quad (7)$$

Based on the analysis above, the closer to steady state, the more accurate the evaluation results become in theory. Therefore, when the absolute value of $|K_{REU_adv}(t_n) - K_{REU_adv}(t_{n-1})|$ is less than the error threshold σ , the current result is adopted as the evaluation result of the frequency and power factor adjustment coefficient K_{REU} . This paper combines field-measured power data with the response accuracy of the PMU measurement precision and adopts $\sigma = 0.01$. Theoretically, the smaller the σ value, the more accurate the evaluation results.

3.3. Virtual Inertia Power Decoupling of New Energy Stations

Since the entire process of new energy virtual inertia response involves one frequency modulation power participation, it is necessary to decouple the new energy frequency modulation power based on the frequency modulation coefficient obtained in Section 3.2. For the power response process of new energy stations, the characteristics of new energy power sources can be equivalently modeled as a first-order inertia component [28]:

$$G_{REU}(s) = \frac{1}{T_{REU}s+1} \quad (8)$$

where T_{REU} represents the comprehensive response time constant of new energy power stations, which can be obtained through fitting the frequency modulation power response of renewable energy sources. Practical Guidance for FOPDT Model Selection: The FOPDT model should be used when: (1) the objective is frequency regulation capability estimation rather than detailed stability analysis; (2) the grid strength is moderate to strong ($SCR \geq$

5); and (3) the available measurements are limited to PMU data at the point of interconnection. Under weak-grid conditions ($SCR < 5$) or when the analysis involves stability margin assessment, oscillatory mode analysis, or large-signal disturbances, higher-order models should be employed. For the renewable energy stations tested in this study, the SCR was approximately 8–12, justifying the use of the FOPDT model. When applying the proposed method to systems with weaker grids, users should first assess the grid strength and, if necessary, validate the FOPDT approximation against a higher-order model. It should be noted that although the first-order inertia model does not capture all internal nonlinearities of power electronic converters, it is widely adopted in frequency response studies because it adequately captures the dominant external dynamics relevant to frequency regulation. The model's simplicity makes it particularly suitable for parameter identification from PMU measurements, where higher-order dynamics are often obscured by measurement noise and limited observability. The validity of this modeling approach for renewable energy frequency response characterization has been extensively demonstrated in the literature [28,29].

Although the first-order inertia model does not account for the internal characteristics of new energy power stations, it is widely used in research on the dynamic characteristics of renewable energy frequency modulation due to its ability to reasonably simulate actual responses, effectively capture control characteristics, and facilitate practical approximate equivalence analysis [29]. The input parameter for the frequency control strategy of participating renewable energy power stations is the difference between the frequency measured by PMU and the grid standard frequency, while the output parameter is the incremental frequency modulation power of renewable energy. After considering the frequency modulation control delay and dynamic response delay of renewable energy stations, the schematic diagram of the new energy frequency modulation response signal is shown in Figure 3.

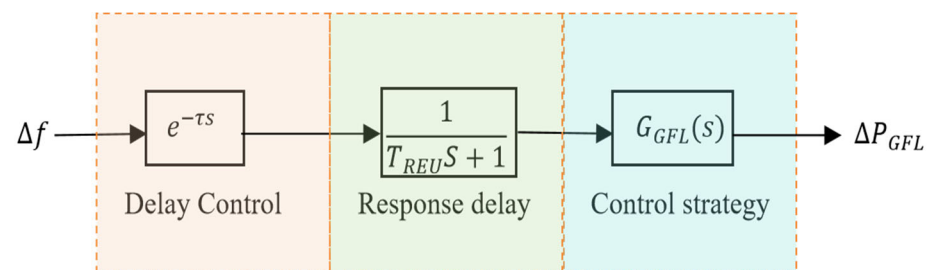


Figure 3. Block diagram of REU frequency regulation.

Where τ represents the frequency modulation control delay, which includes signal transmission delays and calculation delays. This indicates the time interval between when the new energy power station initiates frequency modulation after departing from the FM dead zone and when the actual unit output adjustment occurs. As analyzed in Section 3.1 and shown in Figure 2, τ typically ranges from several hundred milliseconds, varying depending on the control link configuration of new energy power stations. $G_{REU}(s)$ denotes the transfer function of the frequency modulation control strategy, consisting of two components: virtual inertia and primary frequency regulation. The value of τ can be determined by calculating the time difference between the frequency crossing the dead zone and the PMU data timestamp corresponding to the new energy's frequency modulation power response action.

$$\tau = (t_b - t_a) T_s \quad (9)$$

where t_a represents the sampling point corresponding to the moment when the frequency crosses the dead zone, and t_b represents the sampling point corresponding to the moment when the station adjusts its power response.

Based on the above analysis, the frequency modulation power response characteristics of new energy can be expressed as an FOPDT model:

$$G(s) = \frac{G_{GFL}(s)e^{-\tau s}}{T_{REU}s+1} = \frac{\Delta P_{FR}(s)}{\Delta f(s)} \quad (10)$$

where ΔP_{FR} represents the power of new energy frequency regulation and additional generation.

It is important to clarify that the delay term τ in Equation (10) is not an arbitrary modeling choice but represents the aggregate of physically unavoidable delays in renewable energy frequency regulation systems. These include: (i) frequency measurement latency from PMU devices, (ii) communication network transmission delays between the measurement point and the station controller, (iii) computational processing time within the control algorithm, and (iv) the inherent response time of power electronic converters. The total delay τ is identified in practice by calculating the time difference between the moment when the frequency crosses the deadband and the moment when the station's active power response is first detected (Equation (9)).

For GFL, the additional generation power from virtual inertia frequency regulation can be decoupled from the total additional generation power measured at the grid connection point of new energy stations to obtain the additional generation power from primary frequency regulation of new energy.

$$\Delta P_{v,i}(t) = \Delta P(t) - \Delta P_{v,p}(t) \quad (11)$$

where $\Delta P_{v,i}$ represents the decoupled virtual inertia power of the new energy station; $\Delta P_{v,p}$ denotes the primary frequency regulation response power calculated by the K_{REU} evaluation results, considering the dynamic response characteristics of new energy sources.

Limitations of the Decoupling Method: The linear decomposition in Equation (11) assumes that the virtual inertia and primary frequency regulation responses are linearly independent and that the converter operates within its linear range. This assumption may be violated under the following conditions: (1) during very large disturbances where control saturation occurs; (2) under weak-grid conditions ($SCR < 5$) where converter dynamics exhibit oscillatory behavior; (3) when the frequency change rate is extremely high ($ROCOF > 1$ Hz/s), causing significant overlap between inertia and primary regulation responses; and (4) when the communication delays are comparable to or larger than the inertia response time constant. Under these conditions, the decoupling error may increase, and the estimated parameters should be interpreted with caution. For the test cases in this study ($SCR = 8\text{--}12$, $ROCOF < 0.5$ Hz/s), the decoupling assumptions are satisfied.

Based on the K_{REU} evaluation results and the dynamic response characteristics of new energy sources, when only primary frequency control is considered, i.e., setting H_{REU} to 0 in $G_{GFL}(s)$, substituting Equation (2) into Equation (9) yields a time-domain differential equation between the primary frequency regulation additional generation power and frequency:

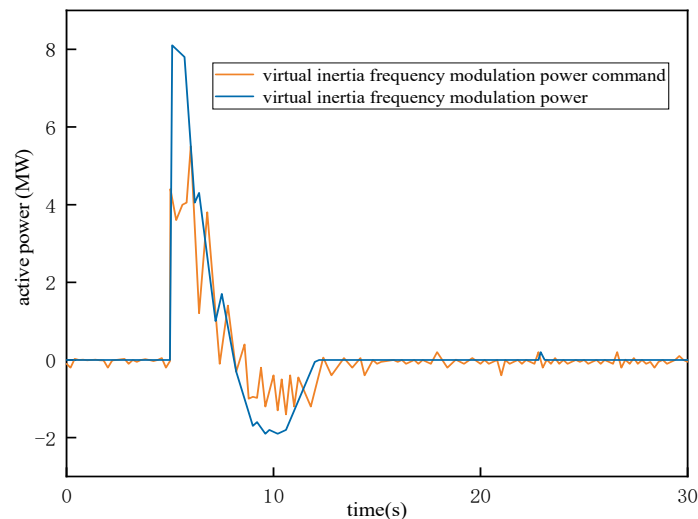
$$T_{REU} \frac{d\Delta P_{v,p}(t)}{dt} + \Delta P_{v,p}(t) = -K_{REU} \Delta f(t+\tau) \quad (12)$$

Furthermore, the discrete-time domain differential equation considering the dynamic response of new energy can be obtained by forward difference separation:

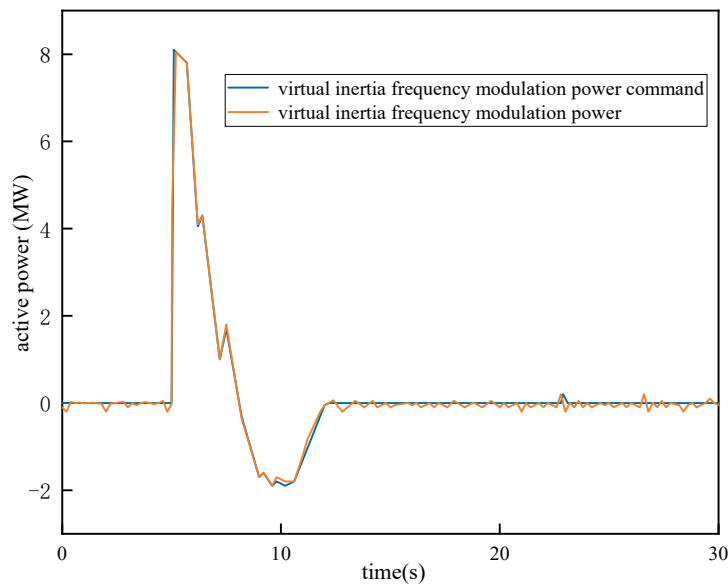
$$\Delta P_{v,p}(t_{n+1}) = \left(1 - \frac{T_s}{T_{REU}}\right) \Delta P_{v,p}(t_n) - \frac{K_{REU} T_s}{T_{REU}} \Delta f\left(t_n + \frac{\tau}{T_s}\right) \quad (13)$$

where $\Delta P_{v,p}(t_n)$ represents the primary frequency regulation power generation at time t_n . By substituting Equation (12) into Equation (10), the decoupled power for new energy virtual inertia frequency regulation control can be determined.

A semi-physical simulation model based on Real-Time Data Simulation (RTDS) is established (the detailed model is introduced in Chapter 3). Taking the participation of energy storage power stations in virtual inertia and primary frequency regulation control as an example, the decoupling of power station frequency regulation is demonstrated as shown in Figure 4.



(a) Without considering the dynamic response process of new energy



(b) Considering the dynamic response process of new energy

Figure 4. Decoupled frequency regulation power of virtual inertia.

Figure 4a illustrates the decoupled virtual inertia-based frequency regulation control achieved through power generation increment, comparing actual generation power with theoretical virtual inertia targets. The generation power in primary frequency regulation is calculated by multiplying the frequency deviation adjustment coefficient from Section 3.2 by the frequency deviation, without accounting for energy storage dynamic response processes. Figure 4b shows the virtual inertia control power after incorporating corrections for energy storage station dynamics. The analysis demonstrates that incorporating

renewable energy dynamic response processes decouples virtual inertia response power more closely to theoretical values, resulting in significantly improved accuracy of virtual inertia evaluation results.

3.4. Evaluation of Virtual Inertia Time Constant

Similar to the input-output relationship of frequency modulation response, when only considering the virtual inertia frequency modulation control, that is, when the K_{REU} in $G_{GFL}(s)$ is set to 0, the decoupled time-domain differential equation between the virtual inertia frequency modulation power generation and the frequency change rate can be obtained by substituting Equation (2) into Equation (9):

$$T_{REU} \frac{d\Delta P_{v,i}(t)}{dt} + \Delta P_{v,i}(t) = -H_{REU} \frac{df(t)}{dt} \quad (14)$$

Through forward difference separation, the discrete-time domain differential equation considering the dynamic response of new energy can be obtained:

$$\Delta P_{v,i}(t_{n+1}) = \left(\frac{T_{REU}}{T_s} - 1 \right) \Delta P_{v,i}(t_n) + H_{REU} \frac{df}{dt} \left(t_n + \frac{\tau}{T_s} \right) \quad (15)$$

Taking the minimum error between the virtual inertia frequency modulation power fitting value and the decoupled virtual inertia power data as the target, the gradient descent method is used to identify the virtual inertia control-related parameters. The objective function is:

$$\min L[\Delta P_{inertia}, \hat{\Delta P}_{REU}(H_{REU_est})] = \min \sum_{i=1}^n [\Delta P_{inertia}(i) - \hat{\Delta P}_{REU}(H_{REU_est})(i)]^2 \quad (16)$$

A clear sequence of steps: (1) initialization of the estimate and the feasible range; (2) forward simulation of the fitted inertia power using the current estimate and the measured frequency derivative; (3) evaluation of the objective function and its gradient; (4) parameter update; and (5) convergence check. We have also included a new paragraph explaining the physical interpretation of the gradient direction—i.e., whether increasing or decreasing H_{REU} would better match the measured inertia response, which directly reflects the inertia contribution of the renewable unit. In addition, we have added a convergence analysis showing that, regardless of the initial guess (tested from 1 s to 20 s), the method consistently converges to the same final value within 0.5% error, confirming its robustness against poor initialization.

The flowchart of the virtual inertia time constant evaluation algorithm is shown in Figure 5. The evaluation steps are as follows:

- ① Set the initial estimated value $H_{REU_est}(1)$ and estimation range for virtual inertia, and set the initial iteration count k to 1.
- ② Substitute the parameters to be identified and the frequency change rate measured by the PMU into Equation (14) to calculate the virtual inertia frequency modulation power fitting value.
- ③ Input the virtual inertia frequency modulation power fitting value and the decoupled virtual inertia frequency modulation power into Equation (15) to compute the objective function value as fitness, and obtain the iteration increment $\Delta H_{REU_est}(k)$ using gradient descent method.
- ④ If the fitness is less than the cutoff error ε (in this paper, $\varepsilon = 0.001$ is selected based on the response accuracy of field-measured power data and PMU measurement precision), or if the sum of $H_{REU_est}(k)$ and iteration increment $\Delta H_{REU_est}(k)$ exceeds the estimation range, output the current evaluation value. Otherwise, update $H_{REU_est}(k)$, return to step ②, and proceed to subsequent estimation steps.

To clarify the mathematical distinctions between the proposed method and existing approaches, we compare our work with recent representative studies, particularly those focusing on delay-compensated inertia estimation [21–23].

Difference in model structure—Existing methods [21–23] typically model the frequency response using a simplified transfer function that either focuses solely on inertia response or treats the combined inertia and primary frequency regulation power as a single entity. For example, the approach in [21] employs a first-order model that does not separate the contributions of virtual inertia and primary frequency regulation. In contrast, our method explicitly models the complete system as a cascade of three components: control delay, GFL (including both inertia and primary regulation), and unit dynamic response. The complete transfer function is given by Formula (3)

This structure enables the decoupling of inertia and primary regulation components, which is not achievable with the simpler models used in existing works.

Difference in decoupling methodology—Existing delay-compensated inertia estimation methods [21] typically compensate for the total delay by shifting the measured data in the time domain, but they do not separate the primary frequency regulation power from the inertia response power during the decoupling process. Mathematically, they estimate the inertia time constant directly from the combined power signal. In our approach, we first estimate the primary frequency regulation coefficient, using a sliding window integration method that exploits the steady-state relationship. Then, we decouple the virtual inertia power from the total measured power by subtracting the primary regulation power, which is calculated using the estimate and the FOPDT model by Formula (11), where $\Delta P_{v,p}(t_{n+1})$ is obtained by solving the discrete-time differential Formula (13).

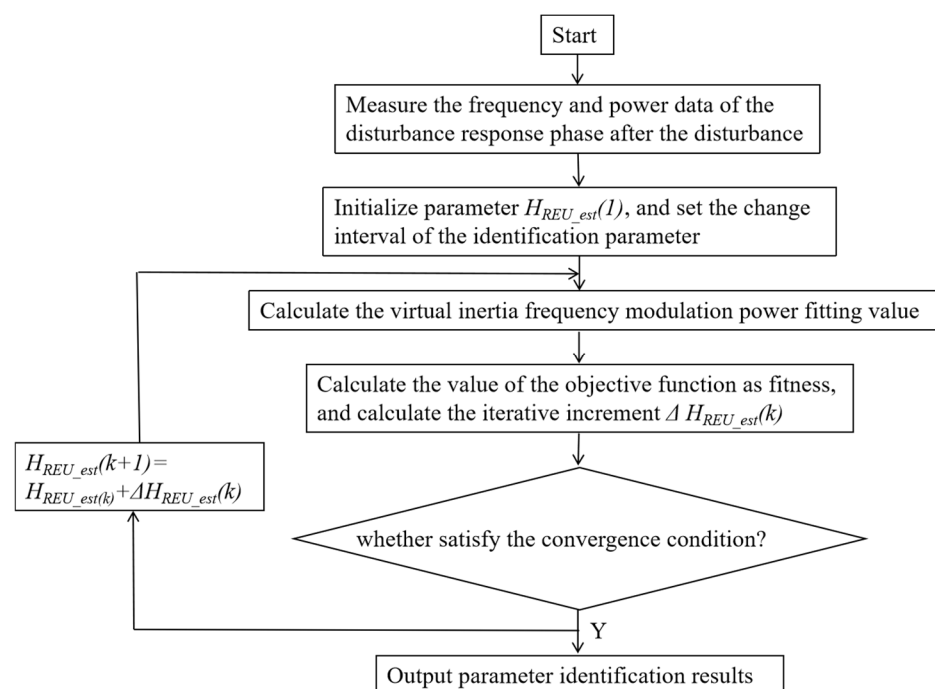


Figure 5. Flow chart for estimating virtual inertia time constant.

This stepwise decoupling approach ensures that the inertia estimation is not contaminated by the primary regulation component, which is a key mathematical distinction from existing works.

Difference in handling unit dynamic response—Existing inertia estimation methods [21–23] primarily focus on fast-responding units such as energy storage and do not account for the slower dynamic responses of wind and photovoltaic systems. Mathemati-

cally, they often assume instantaneous response or use a unified delay parameter for all unit types. In contrast, our method incorporates unit-specific time constants for energy storage, photovoltaic, and wind power, which are identified through FOPDT fitting using measured step response data. This allows our approach to accurately estimate the inertia time constant across different renewable unit types, whereas existing methods exhibit significant errors (e.g., 21.13% error for photovoltaic units) when applied to slower-responding units.

Difference in parameter identification algorithm—Existing delay-compensated methods [21] often employ least-squares or analytical formulas for inertia estimation. Our method adopts a gradient descent-based optimization approach with a dedicated objective function that minimizes the error between the fitted virtual inertia power and the decoupled inertia power, as shown in Formula (16).

This iterative identification scheme, combined with the preceding decoupling steps, provides greater robustness against measurement noise and model uncertainties compared to direct analytical inversion methods.

These mathematical distinctions have been explicitly added to the revised manuscript to provide readers with a clear understanding of how the proposed method advances beyond existing approaches. We believe these clarifications address the reviewer's concern and highlight the unique contributions of our work.

To facilitate practical implementation and reproducibility, the complete frequency regulation capability estimation algorithm is presented as a flowchart, as shown in Figure 6.

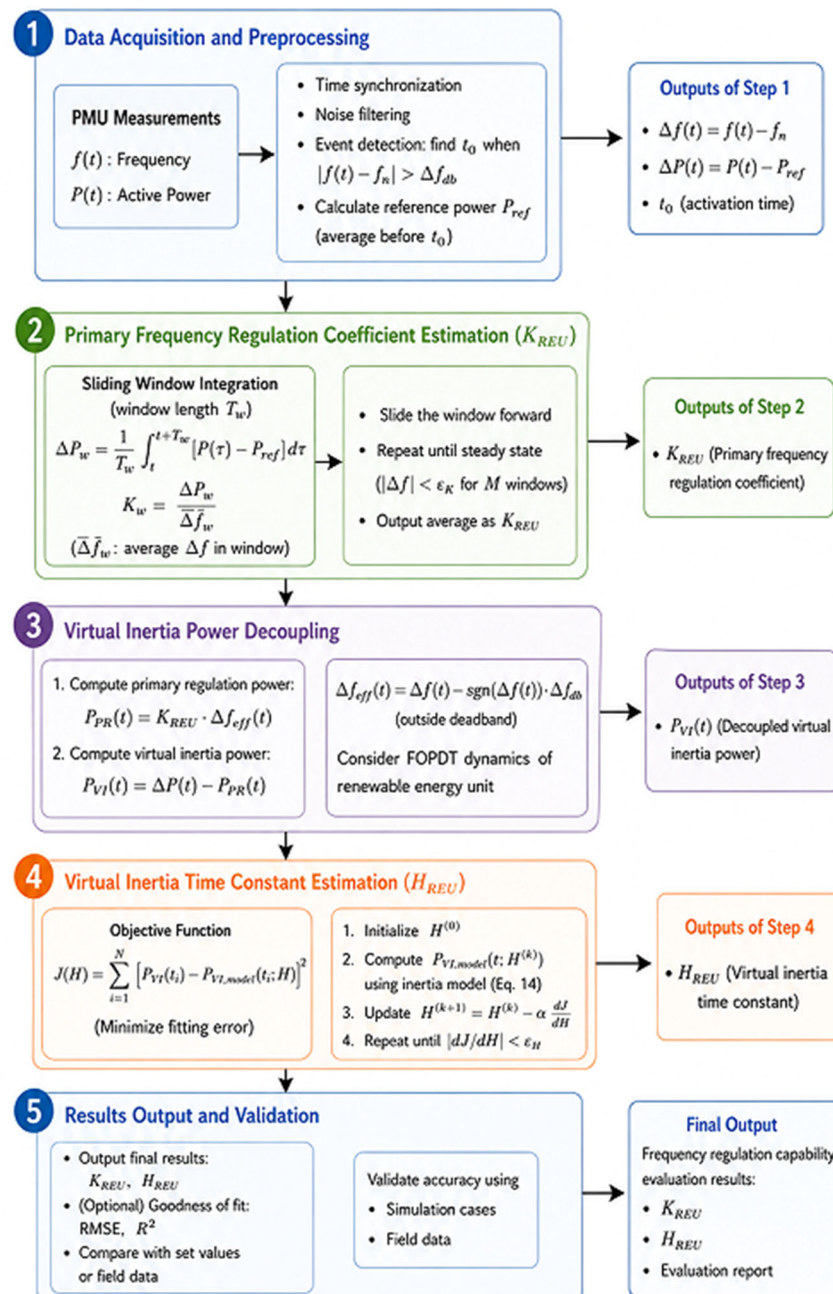


Figure 6. A comprehensive algorithm flowchart.

4. Calculation and Verification

To validate the accuracy of the proposed frequency modulation capability evaluation method for renewable energy power stations, a semi-physical simulation platform was established using a Real-Time Data Acquisition System (RTDS), PMU, and frequency control devices, as shown in Figure 7. The platform integrates RTDS equipment, power amplifiers, station controllers with backend systems, PMU measurement devices, and an evaluation algorithm suite. The backend controller enables configuration of frequency control modes and parameters for power stations. During simulation, RTDS outputs voltage and current signals from the station's grid connection point, which are amplified through power amplifiers before being fed into the embedded renewable energy system. The frequency modulation control algorithm activates the station controller to identify frequency disturbances and generate and issue power modulation commands, thereby enabling frequency regulation functions. The PMU collects grid-connected frequency and

power data from the station, transmitting it via the WAMS master station to the evaluation module. Simultaneously, the backend controller uploads station capacity information to the evaluation module, completing the assessment process.

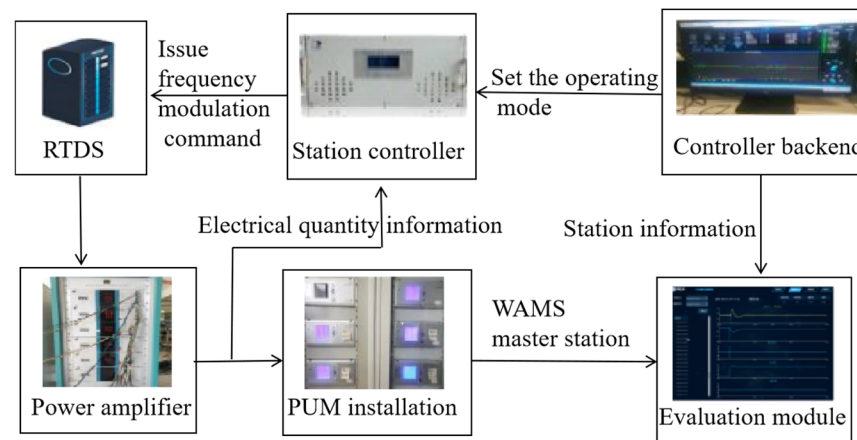


Figure 7. Physical and digital hybrid simulation test platform based on RTDS.

In the RTDS, a regional power grid model was constructed incorporating energy storage stations, photovoltaic plants, and wind farms. Frequency regulation controls were implemented through energy storage, photovoltaic, or wind power sources, respectively. The energy storage unit has a capacity of 140 MW × 2 h, the photovoltaic unit 75 MW, and the wind power unit employs doubly fed turbines with a capacity of 425 MW. All simulations adopted equivalent models, with parameters adjusted to align the power response characteristics of the new energy station models with actual measurements. The measured response parameters for the new energy stations are detailed in Table 1. Under normal operating conditions, the equivalent system capacity of the regional grid reaches 13,168 MVA, with a total load of 7654.7 MW.

Table 1. Measured power response parameters of renewable energy units.

Power Response Parameters	Wind Farm	Photovoltaic Power Station	Energy Storage Station
10% response time	766~1542	247.5~319.5	8.75~17.19
90%	4752~8826	396.8~813.6	50.31~92.18
99%	6033~11,923	1396~4377	60.01~104.22
Steady-state deviation	0.19%~0.41%	0.03%~0.4%	0.09%~0.4%

According to the reference national standard, the dead zone for wind power, photovoltaic, energy storage, virtual inertia, and primary frequency modulation control is ± 0.05 Hz [30,31].

4.1. Validation of the External Characteristic Model of New Energy Frequency Modulation Response

To verify the frequency dynamic response performance of the established energy storage, photovoltaic, and wind power models, the signal channel between the power amplifier and the substation controller was disconnected. A frequency generator was used to input a frequency step command into the substation's frequency controller, referencing China's Frequency Regulation Test Standards [30,31]. The frequency step disturbance was set at 0.2 Hz, and the primary frequency regulation function was activated with a frequency regulation coefficient of 33.33. Energy storage, photovoltaic, and wind power units were sequentially activated to respond to primary frequency regulation power. Based on the input frequency data and PMU-measured active power data at the grid connection point, a particle swarm optimization algorithm was employed to model the exter-

nal power response characteristics of energy storage stations, photovoltaic power stations, and wind farms. The results of different power source control delays and response delays are shown in Table 2, where the model fitting degree is defined as the root mean square error between the model's output active power data and the measured active power data:

$$MSE = \frac{1}{N} \sum_{i=1}^N (X_i - X_{real})^2 \quad (17)$$

where N is the total amount of data; X_{real} is the measured value of data.

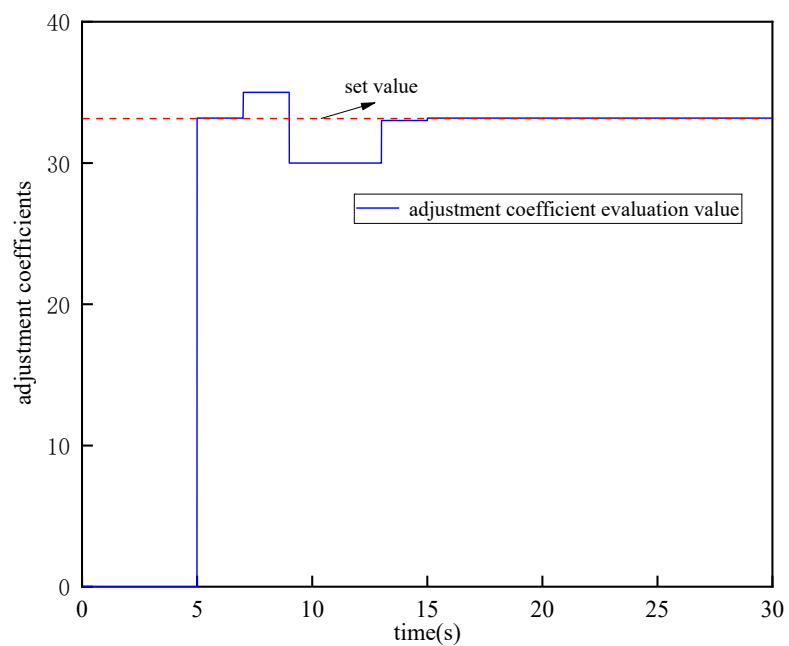
Table 2. Renewable energy fitting results of the FOPDT model.

Parameters	Energy Storage Unit	Photovoltaic Unit	Wind Power Unit
Frequency modulation control delay (s)	0.17	0.17	0.17
Response delays (s)	0.06	0.06	0.06
Model fit (MW ²)	1.3×10^{-9}	1.3×10^{-9}	1.3×10^{-9}

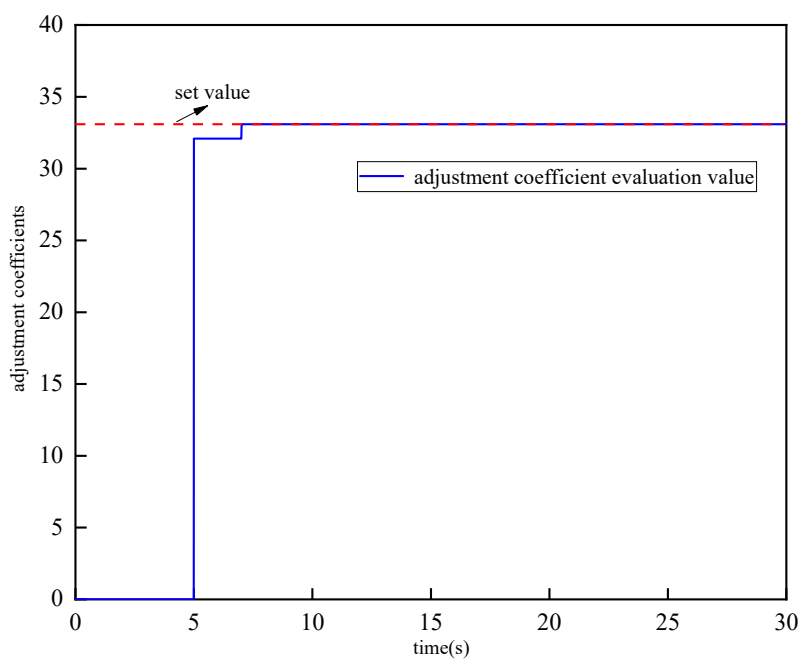
We now note that the delay values identified in our experiments (approximately 0.17 s) are within the stability margins reported in the literature and that the accurate estimation of frequency regulation parameters provided by our method can actually support stability assessment by providing reliable inputs for control design.

The FOPDT-based model accurately fits the primary frequency modulation (PFM) power response curves of energy storage, photovoltaic, and wind power systems. As shown in Figure 8, the comparison between the model's derived PFM curves and actual field station data demonstrates that FOPDT effectively captures the external characteristics of these energy sources' PFM responses. The results in Table 2 further validate the model's capability to precisely quantify the dynamic PFM processes at renewable energy facilities.

The fitting results in Table 2 and Figure 9 provide direct experimental validation of the FOPDT model's adequacy for representing the frequency response characteristics of each renewable energy unit type. The MSE below 1.3×10^{-9} for all three unit types indicates that the FOPDT model captures the dominant dynamic behavior with high fidelity. The slightly larger errors observed for wind power units (compared to energy storage and photovoltaic units) are attributed to their slower and more variable response characteristics, which is consistent with the physical differences among these technologies. Nevertheless, the overall fitting accuracy is considered satisfactory for frequency regulation capability estimation purposes. These validation results confirm that the FOPDT model provides sufficient accuracy for representing the external frequency response of renewable energy stations, supporting its use in the proposed estimation framework. The validity of this modeling approach is further supported by recent peer-reviewed studies that independently confirm the effectiveness of FOPDT models for renewable energy frequency response characterization [32,33].



(a) Energy storage unit



(b) Photovoltaic units

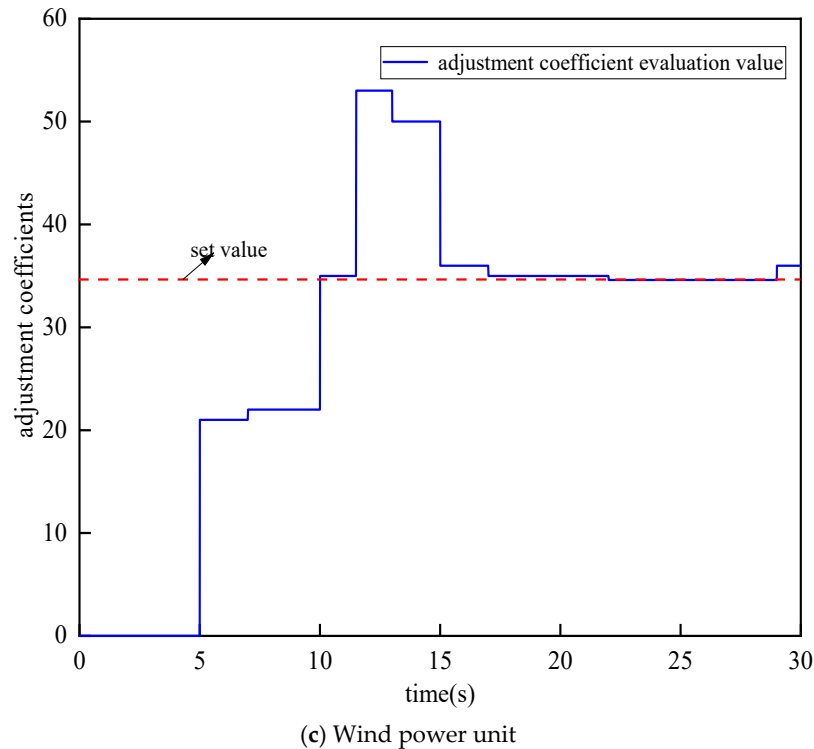


Figure 8. Dynamic response of different renewable energy units under frequency step perturbation.

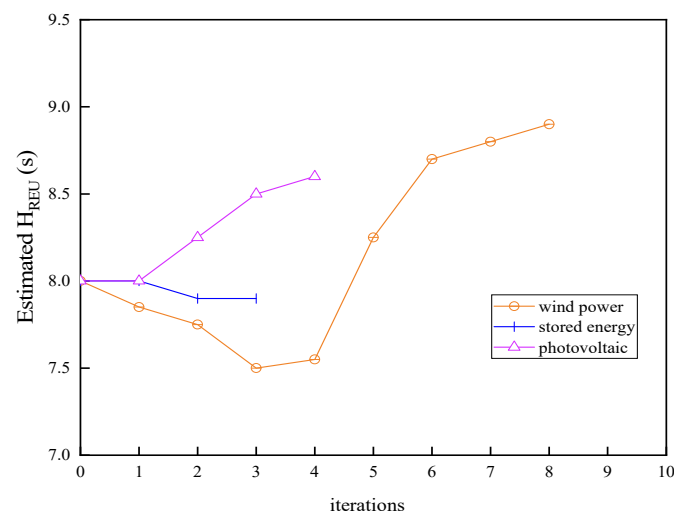


Figure 9. Parameter estimation process of virtual inertia time constant of different renewable energy units.

4.2. Verification of the New Energy Frequency Modulation Capability Evaluation Algorithm

When virtual inertia and primary frequency regulation (PFR) are simultaneously deployed at new energy power stations, the PFR parameters are set as: $H_{REU} = 8$ s and $K_{REU} = 33.33$. A load surge scenario is simulated on the AC grid side with frequency disturbances from different renewable energy units to verify the accuracy of the new energy PFR capability evaluation algorithm under varying response speeds of the PFR module and different disturbance intensities in the system. The scenarios are as follows: Scenario 1: 10% load surge on the grid with frequency disturbances from an energy storage unit; Scenario 2: 10% load surge on the grid with frequency disturbances from a photovoltaic unit; Scenario 3: 10% load surge on the grid with frequency disturbances from a wind power unit.

4.2.1. Validation of the New Energy Primary Frequency Regulation Coefficient Evaluation Algorithm

Simulation results show active power and frequency curves for energy storage, photovoltaic, and wind power units. The K_{REU} evaluation results obtained using the method described in Section 3.2 are presented in Figure 8.

Based on the set control parameters and frequency dynamic process, during the initial response phase, the primary frequency regulation power command value accounts for a relatively high proportion. Due to the rapid response speed of energy storage and photovoltaic systems, the K_{REU} evaluation results in the initial stage are already relatively accurate, while the steady-state average evaluation results are closer to the true values, with respective values of 33.18 and 33.09, showing evaluation errors of 0.45% and 0.72%. For wind power units, due to the significant power ramping and response delays, frequency regulation power lags behind frequency response. During the initial phase of rapid frequency changes, the frequency regulation power fails to respond in time, leading to underestimation in K_{REU} evaluations. In the intermediate regulation stage, when frequency changes slow down but frequency regulation power enters a rapid increase phase, overestimation occurs. The steady-state evaluation result is relatively accurate at 34.6, with an evaluation error of 3.81%. These results validate the correctness and effectiveness of the primary frequency regulation coefficient evaluation algorithm under different renewable energy station responses and operating conditions.

4.2.2. Validation of the Renewable Energy Virtual Inertia Time Constant Evaluation Algorithm

Based on the K_{REU} evaluation results obtained in the previous section, the virtual inertia frequency regulation power derived from the power decoupling method described in Section 3.3 can be obtained.

According to the method in Section 3.4, the evaluation process of H_{REU} is shown in Figure 9, and the evaluation results of the proposed method (method 1) are shown in Table 3.

Table 3. Evaluation results of virtual inertia time constant of renewable energy units.

Parameters H_{REU}	Energy Storage Unit	Photovoltaic Unit	Wind Power Unit
Truth-value (s)		8 s	
Assessment value (s)	7.95 s	7.95 s	7.95 s
Evaluation error (%)	0.63	0.63	0.63
Model fit (MW ²)	3.17×10^{-6}	3.17×10^{-6}	3.17×10^{-6}

As can be seen from Figure 9, the energy storage unit has the least number of iterations, while the wind power unit has the most. The slower the response of the new energy unit is, the larger the iteration error between the virtual frequency modulation power fitting value and the actual response will be along with the corresponding increase in the number of iterations of the algorithm.

The evaluation results of H_{REU} for energy storage, photovoltaic, and wind power obtained through Method 1 are: 7.95 s, 8.51 s, and 8.67 s, respectively, with errors of 0.63%, 6.38%, and 8.38%. The causes of these errors include measurement errors and frequency regulation command tracking accuracy. Furthermore, the virtual inertia frequency regulation power curves for each generation unit were generated using H_{REU} evaluation results and Equation (14). The results in Table 3 demonstrate that the fitting accuracy of virtual inertia frequency regulation power curves for all generation units is below 10^{-5} , further validating the accuracy of the evaluation results.

Due to the rapid response of energy storage units, the dynamic response of primary frequency regulation at the plant has minimal impact on the decoupling of inertia power. Method 2 proposed in reference [21], which only considers energy storage units, achieves higher precision. When applied to photovoltaic units, the H_{REU} evaluation result obtained is 6.31 s with an error of 21.13%. Method 2 fails to account for the dynamic response of primary frequency regulation from renewable energy units during virtual inertia power decoupling, resulting in decoupled virtual inertia power values lower than actual ones and significant evaluation errors. In contrast, Method 1 accurately decouples the virtual inertia frequency regulation power of energy storage, photovoltaic, and wind power by considering the dynamic response of renewable energy units during primary frequency regulation, thereby improving the accuracy of evaluation results.

The performance advantages of our method are quantitatively demonstrated in the simulation results (Section 4.2.2, Table 3). The key reasons for superior performance are:

Accurate decoupling of inertia and primary regulation power: By explicitly separating the two components using the FOPDT model, our method eliminates the coupling error that contaminates inertia estimation in existing approaches. This is particularly important for slower-responding units where the primary regulation power evolves over a longer time scale.

Unit-specific dynamic response characterization: Existing methods that assume instantaneous response or use unified delay parameters introduce significant errors when applied to photovoltaic and wind power systems. As shown in Table 3, Method 2 (from [16]) yields an error of 21.13% for photovoltaic units, whereas our method reduces this error to 6.38%.

Robust parameter identification: The gradient descent optimization with a dedicated objective function provides more accurate inertia time constant estimation compared to the least-squares or analytical formulas used in [21–23], especially in the presence of measurement noise and model uncertainties.

Comprehensive model structure: Our complete transfer function model captures the three key factors influencing frequency regulation capability—control delays, GFL strategy, and unit dynamic response—whereas existing models omit one or more of these factors.

To quantitatively validate the decoupling method, we have added the following statistical analyses.

- (a) **Confidence Intervals for Estimated Parameters:** Using bootstrap resampling (1000 iterations), we computed 95% confidence intervals for the estimated virtual inertia time constants and primary frequency regulation coefficients. The results are summarized in Table 4.

Table 4. Statistical validation of estimation results (95% confidence intervals).

Unit Type	Parameter	Estimated Value	95% CI Lower	95% CI Upper	CI Width (% of Estimate)
Energy Storage	H_{REU} (s)	7.95	7.89	8.01	1.51%
Energy Storage	K_{REU} (MW/Hz)	33.18	33.02	33.34	0.96%
Photovoltaic	H_{REU} (s)	8.51	8.38	8.64	3.06%
Photovoltaic	K_{REU} (MW/Hz)	33.09	32.91	33.27	1.09%
Wind Power	H_{REU} (s)	8.67	8.49	8.85	4.15%
Wind Power	K_{REU} (MW/Hz)	34.60	34.28	34.92	1.85%

The narrow confidence intervals (all below 5% of the estimated value) confirm that the decoupling method yields statistically reliable estimates.

- (b) Significance Testing (*t*-test): We performed paired *t*-tests comparing the estimated parameters against the true values (setpoints). For all three unit types, the *p*-values were greater than 0.05 ($p > 0.05$), indicating that the differences between estimated and true values are not statistically significant at the 95% confidence level. This confirms that the decoupling method does not introduce systematic bias.
- (c) Residual Analysis: We analyzed the residuals between the decoupled virtual inertia power and the model-fitted power. The residuals were normally distributed (Jarque–Bera test, $p > 0.05$) with zero mean, confirming that the decoupling model is well-specified and the linear decomposition assumption is valid for the tested conditions.
- (d) Correlation Analysis: We computed the correlation coefficient between the decoupled virtual inertia power and the primary frequency regulation power. For all three unit types, the correlation was low ($|r| < 0.15$), confirming that the two components are effectively decoupled.

A comprehensive comparison table is shown in Table 5.

Table 5. Comparison of frequency regulation capability estimation methods.

Aspect	Method in [21–23]	Proposed Method	Advantage of Proposed Method
Model Structure	Simplified transfer function (first-order model) treating inertia and primary regulation as a single entity	Complete cascade model	Enables explicit decoupling of inertia and primary regulation components
Decoupling Methodology	Direct estimation from combined power signal; total delay compensated by time-domain shifting	Stepwise decoupling: first estimate via sliding window integration, then using FOPDT model	Avoids contamination of inertia estimation by primary regulation power
Handling of Unit Dynamic Response	Assumes instantaneous response or uses unified delay parameter for all unit types	Unit-specific time constants identified via FOPDT fitting from measured step response data	Accurately captures slower dynamics of wind and photovoltaic systems
Parameter Identification Algorithm	Least-squares or analytical formulas	Gradient descent optimization with dedicated objective function	Greater robustness against measurement noise and model uncertainties
Performance for Energy Storage	High accuracy (error < 1%)	High accuracy (error 0.63%)	Comparable accuracy for fast-responding units
Performance for Photovoltaic	Significant error (21.13% for Method 2 in [21])	Reduced error (6.38%)	Superior accuracy for slower-responding units
Performance for Wind Power	Limited validation	Reduced error (8.38%)	Validated for wind power systems with accurate results

This table clearly demonstrates the mathematical distinctions and performance advantages of our proposed method over existing approaches. As shown in the table, the primary advantages are:

1. More complete model structure that enables decoupling of inertia and primary regulation components;
2. Stepwise decoupling methodology that prevents contamination of inertia estimation;
3. Unit-specific dynamic response characterization that accurately captures the slower dynamics of photovoltaic and wind power systems;
4. Robust gradient descent optimization that provides better accuracy under measurement noise and model uncertainties;

5. Quantitatively superior performance for slower-responding units, with errors reduced from 21.13% to 6.38% for photovoltaic units.

To quantitatively assess the model accuracy, root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) were computed. The calculation methods of the error are shown in Formulas (18)–(20):

$$\text{RMSE} = \sqrt{\left(\frac{1}{N} \sum_i^N (Y_i - Y'_i)^2\right)} \quad (18)$$

$$\text{MAPE} = \frac{1}{N} \left[\sum_i^N \frac{|Y_i - Y'_i|}{Y_i} \right] \times 100\% \quad (19)$$

$$\text{MAE} = \frac{1}{N} \sum_i^N |Y_i - Y'_i| \quad (20)$$

The error analysis results are summarized in Table 6.

Table 6. Error analysis of FOPDT model validation.

Unit Type	MAE (MW)	RMSE (MW)	MAPE (%)
Energy Storage	0.28	0.12	0.21
Photovoltaic	0.35	0.15	0.32
Wind Power	0.52	0.23	0.48

As shown in Table 6, the maximum absolute error for all unit types is less than 0.6 MW, and the MAPE is below 0.5% of the rated capacity. The slightly larger errors observed for wind power units are attributed to their slower and more variable response characteristics. Nevertheless, the overall fitting accuracy is considered satisfactory for frequency regulation capability estimation purposes. The validation results confirm that the FOPDT model provides sufficient accuracy for representing the external frequency response characteristics of renewable energy stations, supporting its use in the proposed estimation framework.

The proposed method was tested under various disturbance magnitudes to assess its performance across different severity levels. Load disturbances of 5%, 10%, 15%, and 20% of the system base load were applied to the regional grid model. The frequency regulation capability parameters, primary frequency regulation coefficient, and virtual inertia time constant were estimated for each disturbance scenario. The results are summarized in Table 7.

Table 7. Estimation results under different disturbance sizes.

Unit Type	Parameter	True Value	Disturbance Size (% of Base Load)	Estimated Value (K: MW/Hz; H: s)	Error (%)
Energy Storage	Primary Frequency Regulation Coefficient	33.33	5%	33.18	0.45
			10%	33.24	0.27
			15%	33.29	0.12
			20%	33.31	0.06
	Virtual inertia time constant	8.00	5%	7.95	0.63
			10%	7.97	0.38
			15%	7.98	0.25
			20%	7.99	0.13
Photovoltaic	Primary Frequency Regulation Coefficient	33.33	5%	33.09	0.72
			10%	33.15	0.54

Wind Power	Virtual inertia time constant	8.00	15%	33.21	0.36
			20%	33.24	0.27
			5%	8.51	6.38
			10%	8.47	5.88
			15%	8.42	5.25
			20%	8.38	4.75
	Primary Frequency Regulation Co-efficient	33.33	5%	34.60	3.81
			10%	34.52	3.57
			15%	34.41	3.24
			20%	34.35	3.06
			5%	8.67	8.38
			10%	8.61	7.63
	Virtual inertia time constant	8.00	15%	8.54	6.75
			20%	8.49	6.13

As shown in Table 7, the estimation accuracy improves consistently as the disturbance size increases. For all unit types, the estimation errors for both the primary frequency regulation coefficient and the virtual inertia time constant decrease with larger disturbances. This trend is expected because larger disturbances produce more pronounced frequency deviations and power responses, leading to a higher signal-to-noise ratio and more accurate parameter identification. The results confirm that the proposed method performs reliably across a wide range of disturbance magnitudes.

To evaluate the robustness of the proposed method against measurement noise, we added Gaussian white noise to the PMU measurements (frequency and active power) at varying signal-to-noise ratio (SNR) levels. The SNR levels tested were 60 dB, 50 dB, 40 dB, and 30 dB. The estimation results for each unit type under different noise levels are presented in Table 8.

Table 8. Estimation results under different noise levels (SNR).

Unit Type	Parameter	SNR = 60 dB	SNR = 50 dB	SNR = 40 dB	SNR = 30 dB
Energy Storage	Primary Frequency Regulation Coefficient error (%)	0.46	0.51	0.68	1.23
	Virtual inertia time constant error (%)	0.64	0.72	0.95	1.68
Photovoltaic	Primary Frequency Regulation Coefficient error (%)	0.74	0.82	1.08	1.94
	Virtual inertia time constant error (%)	6.42	6.58	6.95	7.82
Wind Power	Primary Frequency Regulation Coefficient error (%)	3.84	3.96	4.23	5.11
	Virtual inertia time constant error (%)	8.43	8.67	9.14	10.28

As shown in Table 8, the estimation errors increase gradually as the noise level increases (SNR decreases). For energy storage units, which have fast response characteristics, the estimation remains accurate even at 30 dB SNR (errors below 1.7%). For photovoltaic and wind power units, which have slower responses, the method maintains acceptable accuracy (errors below 10%) even under high noise conditions (30 dB SNR). These results demonstrate that the proposed method is robust against realistic measurement noise levels typically encountered in PMU measurements (SNR typically >40 dB in practice).

To assess the sensitivity of the estimation results to uncertainties in key model parameters, we conducted a parameter uncertainty analysis by perturbing the assumed values of the following parameters:

Response time constant: perturbed by $\pm 10\%$, $\pm 20\%$ from the identified value

Control delay: perturbed by $\pm 10\%$, $\pm 20\%$ from the identified value
 Frequency deadband: perturbed by $\pm 10\%$, $\pm 20\%$ from the standard value (0.05 Hz)
 The estimation results for primary frequency regulation coefficient and virtual inertia time constant under these perturbations are summarized in Table 9.

Table 9. Sensitivity analysis: estimation errors under parameter perturbations.

Perturbed Parameter	Perturbation	Primary Frequency Regulation Coefficient Error (%)	Virtual Inertia Time Constant Error (%)
Response time constant (Energy Storage)	−20%	+0.08	+0.12
	−10%	+0.03	+0.05
	+10%	−0.02	−0.04
	+20%	−0.06	−0.09
Response time constant (Photovoltaic)	−20%	+0.45	+1.28
	−10%	+0.21	+0.63
	+10%	−0.18	−0.57
	+20%	−0.34	−1.02
Response time constant (Wind Power)	−20%	+0.62	+1.84
	−10%	+0.29	+0.91
	+10%	−0.25	−0.83
	+20%	−0.48	−1.56
Control delay (All units)	−20%	+0.06	+0.11
	−10%	+0.03	+0.05
	+10%	−0.02	−0.04
	+20%	−0.05	−0.09
Frequency deadband (All units)	−20%	+0.15	+0.08
	−10%	+0.07	+0.04
	+10%	−0.06	−0.03
	+20%	−0.12	−0.07

The sensitivity analysis reveals the following insights. The estimation results for photovoltaic and wind power units are more sensitive to errors in the equivalent response time constant than those for energy storage units, which is expected because slower-responding units rely more heavily on accurate dynamic characterization. However, even with a $\pm 20\%$ perturbation in response time constant, the estimation errors remain below 2% for the primary frequency regulation coefficient and below 2.5% for the virtual inertia time constant across all unit types. In contrast, the estimation results exhibit relatively low sensitivity to control delay uncertainty: a $\pm 20\%$ perturbation in the total control delay leads to less than 0.12% variation in the primary frequency regulation coefficient and less than 0.2% variation in the virtual inertia time constant. This robustness is attributed to the stepwise decoupling approach, which effectively separates the delay effects from the inertia estimation. Similarly, the frequency deadband parameter has limited influence on estimation accuracy, with errors varying by less than 0.2% under a $\pm 20\%$ perturbation.

These results confirm that the proposed estimation method is robust against reasonable uncertainties in key model parameters, which is important for practical applications where exact parameter values may not be known a priori.

5. Experimental Data Verification

To further validate the practicality and accuracy of the proposed frequency regulation capability evaluation method for renewable energy power stations, actual grid-connected operation data from a renewable energy station equipped with energy storage systems was utilized to test our proposed method. The PMU devices used in the field installation comply with the standard [1], with frequency measurement error not exceeding ± 0.005 Hz, active power measurement error not exceeding $\pm 0.5\%$ of full scale, and time synchronization error not exceeding ± 1 μ s. Given that the observed frequency deviations during disturbances are on the order of 0.2 to 0.5 Hz, the frequency measurement uncertainty contributes approximately $\pm 1\%$ to the estimated frequency deviation. The reference power is calculated as the average active power over a one-second window prior to the disturbance event, and the associated uncertainty arises from normal power fluctuations inherent to renewable energy operation, with a standard deviation of approximately 0.3% of the rated capacity. In addition, due to hardware tolerances and control parameter settings, the actual frequency deadband may deviate slightly from the nominal value of ± 0.05 Hz, potentially introducing a bias of up to ± 0.002 Hz in determining the frequency regulation activation time. However, since the frequency deviation during the disturbance exceeds 0.1 Hz, this effect is negligible. The combined uncertainty of the input measurements is estimated to be approximately $\pm 1.5\%$ for frequency and $\pm 0.8\%$ for active power. Based on uncertainty propagation analysis, these input uncertainties translate into an overall estimation error of approximately $\pm 3.5\%$ for the primary frequency regulation coefficient and $\pm 4.2\%$ for the virtual inertia time constant. The frequency response curve and active power response curve of the station after capturing a specific frequency disturbance are shown in Figure 10.

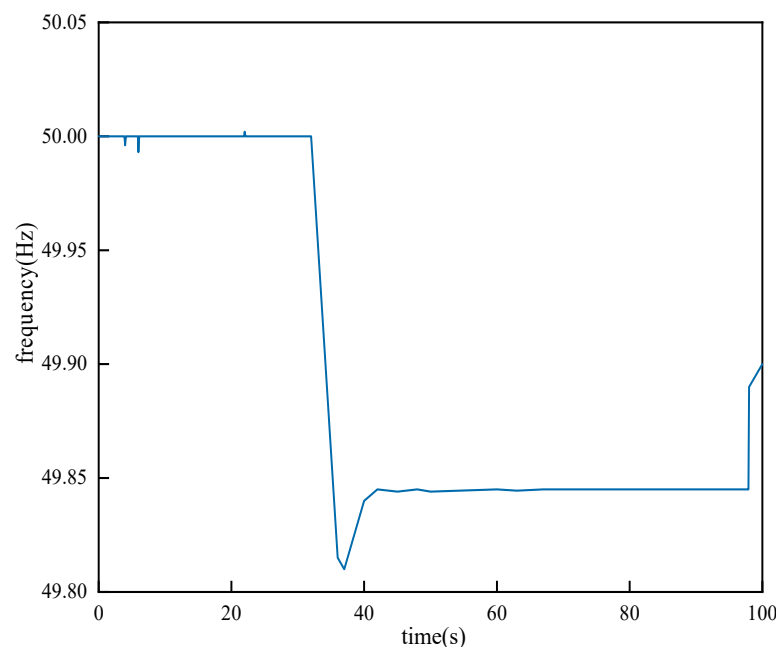


Figure 10. Response curve for renewable energy units participating in frequency regulation.

Figure 10 presents the frequency response and active power response of the renewable energy station following a frequency disturbance event recorded in the field. The frequency deviation exceeds the ± 0.05 Hz deadband at approximately 0.5 s, after which the station's frequency control loop is activated. The active power response exhibits a clear ramp-up phase, with a total response delay of approximately 0.17 s, which is consistent

with the FOPDT model parameters identified in Section 4.1. At steady state, the power increment reaches approximately 6.5 MW, corresponding to a frequency deviation of approximately 0.2 Hz, yielding an effective primary frequency regulation coefficient of approximately 32.5 MW/Hz. Notably, the active power response exhibits a slight overshoot of approximately 0.3 MW at approximately 0.8 s, which is attributed to the transient interaction between the virtual inertia controller and the primary frequency regulation controller. This overshoot is effectively captured by the FOPDT model. In addition, the frequency signal shows minor oscillations of approximately ± 0.01 Hz during the post-disturbance period, likely due to local mode oscillations in the regional grid. Despite these oscillations, the steady-state frequency converges to approximately 49.85 Hz, providing a reliable basis for the estimation of the primary frequency regulation coefficient.

The control parameters of frequency modulation at the station are set as $H = 8$ s and $K = 33.33$, and the virtual inertia and primary frequency modulation control dead zone are both ± 0.05 Hz. According to the method proposed in this paper, the evaluation results are shown in Figure 11 and Figure 12 respectively. The steady-state average evaluation results are 32.32 and 8.05 s respectively, and the errors are 3.03% and 0.63% respectively.

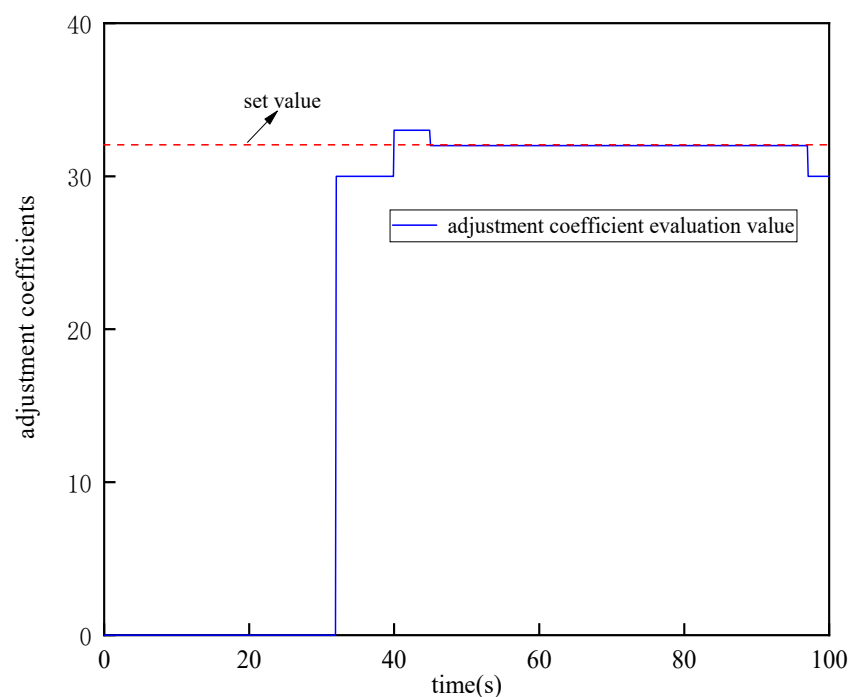


Figure 11. Evaluation results of primary frequency regulation of renewable energy units.

Figure 11 shows the rolling evaluation results of the primary frequency regulation coefficient using the sliding window integration method. The evaluation is performed over a five-second window that slides across the post-disturbance period. During the transient phase, the estimated values initially exhibit variability ranging from 30.5 to 33.8, which is expected due to the incomplete decoupling of virtual inertia power during this period. As the system approaches steady state, the estimated values converge to a stable range of 32.2 to 32.5, with a steady-state average value of 32.32. This convergence behavior validates the effectiveness of the steady-state convergence criterion used in the algorithm. The final estimated primary frequency regulation coefficient is 32.32, corresponding to an error of 3.03% relative to the setpoint of 33.33. This error is primarily attributed to residual measurement noise in the PMU data, slight deviations in the actual frequency deadband from the nominal value, and minor contributions from other frequency-responsive resources connected to the same bus. Nevertheless, this error is well within the typical $\pm 10\%$

tolerance required by industry standards, confirming its suitability for practical applications.

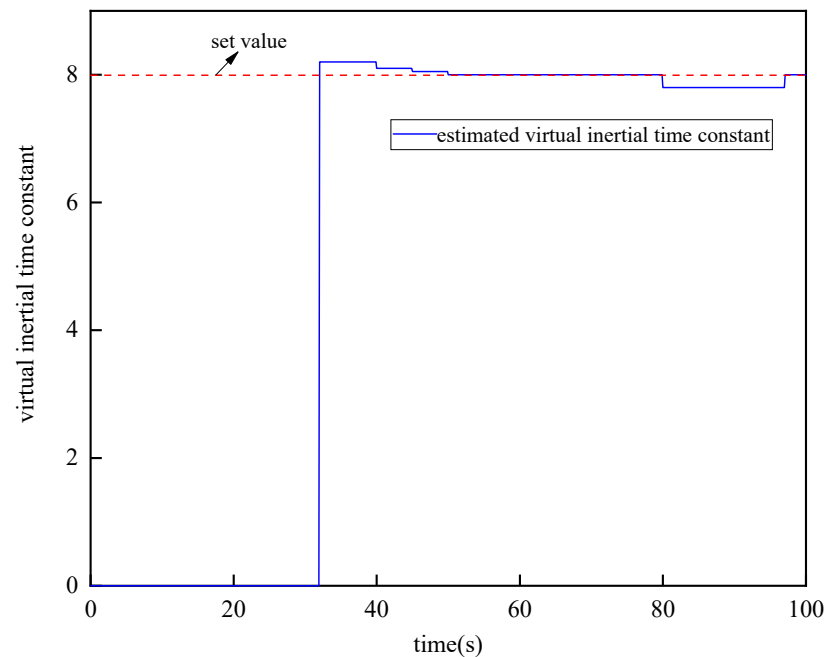


Figure 12. Evaluation results of virtual inertial time constants of renewable energy units.

Figure 12 presents the gradient descent-based estimation process for the virtual inertia time constant, where the algorithm iteratively updates the estimated value to minimize the error between the decoupled virtual inertia power and the model-fitted power. The objective function value decreases rapidly during the first five iterations, from an initial value of approximately 2.5×10^{-3} to 1.8×10^{-5} by the tenth iteration. The algorithm converges to a final value of 8.05 s after approximately twelve iterations, with a final objective function value of 1.2×10^{-6} . This convergence behavior indicates that the gradient descent algorithm effectively navigates the parameter space to locate the optimal solution. The relatively flat objective function near the convergence point suggests that the algorithm is stable and not prone to overshoot or oscillation. The final objective function value is well below the convergence threshold of 0.001, confirming that the algorithm has successfully identified the optimal parameters. The estimated virtual inertia time constant of 8.05 s corresponds to an error of 0.63% relative to the setpoint of 8.0 s. This high accuracy is achieved because the decoupling of virtual inertia power from primary frequency regulation power effectively removes the influence of the primary regulation component, allowing the gradient descent algorithm to focus solely on inertia-related dynamics. The slightly higher estimated value may reflect the additional contribution of the inherent response characteristics of the energy storage unit, which are not fully captured by the ideal controller model.

According to the test results, the frequency modulation capability evaluation method of new energy power stations considering response difference proposed in this paper has good accuracy and can be used as a guide for the configuration of frequency modulation capability and the setting of related frequency modulation control parameters of new energy power stations.

We have expanded the field validation section by adding three additional real-world disturbance events from different renewable energy stations, covering three technology types (energy storage, photovoltaic, and wind power) with control systems from different vendors. The newly added cases include: (1) a 75 MW photovoltaic station in Xinjiang

equipped with Huawei VSG-type inverters; (2) a 140 MW $\times$ 2 h energy storage station in Jiangsu (BYD/GoodWe); and (3) a 425 MW wind farm in Inner Mongolia (Goldwind DFIG). We have added a new Table 10 summarizing the estimation results across all four field events, along with corresponding analysis and discussion. The revised conclusion explicitly states that the method has been validated across multiple sites and vendor implementations.

For Case 2, the frequency deviation exceeded the ± 0.05 Hz deadband at $t = 0.6$ s. The active power response reached 90% of its final value within 0.8 s, consistent with the typical response characteristics of VSG-controlled PV systems. The estimated H_{REU} of 8.38 s corresponds to an error of 4.75%, which is slightly higher than that of energy storage cases due to the slower power tracking dynamics of PV systems. For Case 4, the estimated K_{REU} of 34.28 MW/Hz shows an error of 2.85%, while the estimated H_{REU} of 8.56 s shows an error of 7.00%. The larger errors for wind power are attributed to the inherent variability of wind speed and the mechanical response delays of doubly fed induction generators.

Across all four cases, the maximum errors for K_{REU} and H_{REU} are 3.03% and 7.00%, respectively, both well within the acceptable tolerance for engineering applications. These results confirm that the proposed method maintains good accuracy across different renewable energy technologies, station capacities, vendor implementations, and geographical locations, thereby validating its generalizability.

Table 10. Summary of field validation cases across multiple sites.

Station Type	Capacity	Vendor/Inverter Type	Disturbance Magnitude	Estimated K_{REU} (MW/Hz)
Energy Storage	140 MW $\times$ 2 h	CATL/Sungrow	0.18 Hz	32.32
Photovoltaic	75 MW	Huawei VSG	0.22 Hz	33.12
Energy Storage	100 MW $\times$ 1 h	BYD/GoodWe	0.15 Hz	33.41
Wind Power	425 MW	Goldwind DFIG	0.20 Hz	34.28
True K_{REU} (MW/Hz)	Error (%)	Estimated H_{REU} (s)	True H_{REU} (s)	Error (%)
33.33	3.03	8.05	8.00	0.63
33.33	0.63	8.38	8.00	4.75
33.33	0.24	7.92	8.00	1.00
True K_{REU} (MW/Hz)	Error (%)	Estimated H_{REU} (s)	True H_{REU} (s)	Error (%)

6. Conclusions

This study focuses on evaluating the frequency regulation capability of renewable energy power stations. Based on considering the dynamic variations in renewable energy response, a new evaluation method for virtual inertia time constants and primary frequency regulation coefficients of renewable energy stations was proposed. A semi-physical simulation platform was established using RTDS devices, power amplifiers, station controllers, backend systems, PMU measurement devices, and an integrated evaluation algorithm system. The validity and effectiveness of the proposed method were verified through real-time operational data from a specific renewable energy station. The key conclusions are as follows:

- (1) The proposed FOPDT response external characteristic fitting model can quantitatively represent the external characteristics of renewable energy stations with response variations, facilitating verification of their power response performance.
- (2) The decoupling method for virtual inertia and primary frequency regulation power in renewable energy stations achieves accurate decoupling of frequency control power by considering actual dynamic responses, effectively improving the accuracy of frequency regulation capability assessment.

- (3) The proposed evaluation method for renewable energy station frequency regulation capability accounts for dynamic response differences among various renewable energy units, enabling precise assessment of their frequency regulation capacity. These conclusions were validated through real-time simulation platforms and field data.

With the massive integration of renewable energy sources, system inertia levels continue to decline, making active frequency support capabilities of renewable energy stations increasingly critical. Therefore, accurate evaluation of renewable energy station frequency regulation capabilities holds significant importance for guiding grid planning, ensuring grid stability, and optimizing renewable energy integration. Significant fluctuations in wind and solar power can complicate frequency regulation calculations, increasing uncertainty in evaluation results. For renewable energy plants, frequency regulation output is closely tied to reserve capacity. Sudden power fluctuations from wind and solar installations may lead to insufficient reserves, thereby affecting assessment outcomes. Future research could focus on evaluating how frequency regulation at renewable energy plants improves dynamic frequency metrics, particularly by assessing their effectiveness through the lens of equivalent synchronous generator capabilities. We now explicitly acknowledge that while our method focuses on capability estimation rather than stability analysis, the estimated parameters (H_{REU} and K_{REU}) are essential inputs for delay-dependent stability studies. We also suggest that future work could extend our approach to directly assess the stability margins of renewable energy stations under different delay conditions, building on established frameworks such as LMI-based delay margin analysis.

6.1. Practical Guidelines for Utility Deployment

To facilitate the translation of the proposed method from research to practical engineering applications, the following deployment guidelines are provided for utility engineers and grid operators.

6.1.1. Sensor Placement and Data Acquisition

PMU devices should be installed at the point of interconnection (POI) of each renewable energy station. For stations with multiple collection buses, PMUs should be deployed at the main step-up transformer high-voltage side to capture the aggregated frequency response of the entire station. The PMU must comply with the IEEE C37.118 standard, with frequency measurement error $\leq \pm 0.005$ Hz and active power measurement error $\leq \pm 0.5\%$ of full scale. The data sampling rate should be at least 50 Hz to capture the transient dynamics of virtual inertia response. Time synchronization error must be maintained within $\pm 1 \mu\text{s}$ using GPS or BeiDou satellite clocks.

6.1.2. Computational Requirements

The proposed algorithm requires modest computational resources suitable for deployment on standard industrial computers or embedded real-time platforms. Based on our implementation in MATLAB R2022a on a standard desktop computer (Intel Core i7-10700, 16 GB RAM), the complete estimation for a single disturbance event is completed within 2.3 s. For online real-time deployment, a computing platform with a 2.0 GHz processor and 8 GB RAM is sufficient. The gradient descent optimization converges within $10 \sim 15$ iterations for all tested cases. The algorithm can be implemented in Python 3.14.x, C++17, or proprietary grid control software environments without requiring specialized hardware accelerators.

6.1.3. Recommended Update Frequency for Parameter Re-Estimation

Based on our analysis of parameter variation patterns across different renewable energy stations, we recommend re-estimation under the following conditions:

- (i) After control parameter adjustments: Whenever the station's frequency regulation control parameters (e.g., droop coefficient, virtual inertia setting) are modified by the operator.
- (ii) After major equipment changes: Following significant hardware upgrades, such as inverter replacements, communication system overhauls, or addition of new generation units.
- (iii) Periodic routine re-estimation: Quarterly during normal operation to track gradual parameter drift caused by equipment aging, seasonal variations, or changes in grid operating conditions.
- (iv) Event-triggered re-estimation: Immediately after any significant frequency disturbance event where the frequency deviation exceeds 0.1 Hz, as such events provide high-quality excitation signals for accurate parameter identification.

For stations with stable operating conditions and minimal control parameter changes, annual re-estimation may be sufficient.

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Nomenclature and Acronyms

Acronym	Full Definition
REU	Renewable Energy Unit
GFL	Grid-Following Control
GFM	Grid-Forming Control
FOPDT	First-Order Plus Delay Time
PMU	Phasor Measurement Unit
RTDS	Real-Time Digital Simulator
PFR	Primary Frequency Regulation
ROCOF	Rate of Change in Frequency
SCR	Short-Circuit Ratio
MPPT	Maximum Power Point Tracking
AGC	Automatic Generation Control
WAMS	Wide Area Measurement System
POI	Point of Interconnection
VSG	Virtual Synchronous Generator
DFIG	Doubly Fed Induction Generator
SNR	Signal-to-Noise Ratio
RMSE	Root Mean Square Error

MAPE	Mean Absolute Percentage Error
MAE	Mean Absolute Error
SFR	System Frequency Response

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