

Article

Research on the Data-Driven Identification of Control Parameters for Voltage Ride-Through in Energy Storage Systems

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Abstract

The large-scale integration of wind power, photovoltaic systems, and energy storage systems (ESSs) into power grids has increasingly influenced the transient stability of power systems due to their dynamic response characteristics. Considering the commercial confidentiality of core control parameters from equipment manufacturers, parameter identification has become a crucial approach for analyzing ESS dynamic behaviors during high-voltage ride-through (HVRT) and low-voltage ride-through (LVRT) and for optimizing control strategies. In this study, we present a multidimensional feature-integrated parameter identification framework for ESSs, combining a multi-scenario voltage disturbance testing environment built on a real-time laboratory platform with field-measured data and enhanced optimization algorithms. Focusing on the control characteristics of energy storage converters, a non-intrusive identification method for grid-connected control parameters is proposed based on dynamic trajectory feature extraction and a hybrid optimization algorithm that integrates an improved particle swarm optimization (PSO) algorithm with gradient-based coordination. The results demonstrate that the proposed approach effectively captures the dynamic coupling mechanisms of ESSs under dual-mode operation (charging and discharging) and voltage fluctuations. By relying on measured data for parameter inversion, the method circumvents the limitations posed by commercial confidentiality, providing a novel technical pathway to enhance the fault ride-through (FRT) performance of energy storage systems (ESSs). In addition, the developed simulation verification framework serves as a valuable tool for security analysis in power systems with high renewable energy penetration.

Keywords: LVRT; HVRT; ESS; parameter identification; multi-algorithm fusion analysis; MT 6040 simulator



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1. Introduction

Under the “Dual Carbon” policy objectives, ESSs have become indispensable components in power systems with high renewable energy penetration, owing to their flexible power regulation capabilities [1–3]. With the widespread adoption of grid-forming control and millisecond-level inertia response technologies, the dynamic characteristics of ESSs during voltage/frequency emergency support scenarios directly impact grid transient

stability [4,5]. However, the control logic of energy storage converters (PCS) is highly complex, and the nonlinear coupling mechanisms between HVRT/LVRT parameters and dynamic responses remain insufficiently resolved, resulting in significant discrepancies between simulation models and actual device behaviors, posing risks to grid security.

The FRT process of energy storage systems involves dynamic interactions across multiple timescale control loops. However, the core control parameters—such as converter PI controller gains and reactive power compensation slopes—are typically subject to commercial confidentiality restrictions imposed by manufacturers. The authors of existing studies primarily rely on idealized assumptions or simplified equivalent models for parameter identification, which fail to capture the transient coupling effects under real-world operating conditions (e.g., control loop interference caused by sudden power fluctuations), leading to insufficient accuracy in parameter inversion and significantly hindering the reliability assessment of energy storage systems in providing active grid support [6–9].

The authors of recent studies on parameter identification in energy storage systems have mainly focused on batteries and electrochemical characteristics. For instance, the authors of References [10,11] developed improved battery cell models that incorporate effects such as capacity degradation, ambient temperature, and current rate, forming the basis for state-of-charge (SOC) estimation in lithium batteries. The authors of Reference [12] identify parameters to produce a more accurate electrochemical model of lithium-ion batteries. In [13], a bias-compensated least-squares method is proposed for online parameter identification to develop a high-fidelity dynamic model of lithium batteries. The authors of Reference [14] introduce a new state estimation method for lead–carbon batteries based on the relationship between the open-circuit voltage and available energy at full discharge. In addition, the authors of [15] utilize a polynomial fitting approach to identify the system's inertia coefficient by fitting the measured power and frequency data at the point of common coupling. The results of the above studies reveal a clear research gap in identifying the control parameters of energy storage converters.

Conventional parameter identification methods—such as frequency sweep analysis, single-objective gradient-based optimization, and least-squares techniques—present notable limitations [16–21]:

1. They rely heavily on prior knowledge of internal device models, making them incompatible with the “black-box” nature of commercial energy storage converter control strategies;
2. They struggle to capture the divergent dynamic trajectories induced by charge/discharge mode switching, resulting in poor parameter generalization;
3. Single optimization algorithms often fall into local optima, making it challenging to achieve parameter compatibility across multiple scenarios, such as HVRT and LVRT.

Accurate identification of the FRT control parameters in ESSs through measurement-driven methods has emerged as a critical challenge for enhancing the credibility of digital simulations in renewable energy power systems.

To address these challenges, we propose a measurement-driven parameter identification method for FRT control in ESSs, which integrates dynamic trajectory feature extraction with a hybrid optimization algorithm [22]. The main contributions of this work can be summarized as follows:

1. A measurement-driven, non-intrusive identification approach is developed, offering an engineering-oriented solution for ESS modeling under commercial confidentiality constraints;
2. A trajectory segmentation identification mechanism compatible with both charging and discharging modes is proposed to address parameter coupling issues caused by control logic switching;

3. A hybrid optimization framework is established under multi-objective constraints of HVRT/LVRT scenarios, improving parameter adaptability in complex fault conditions.

First, an HVRT/LVRT testing environment is established using the real-time laboratory platform of the MT 6040 Simulator which is produced by ModelingTech Energy Technology Co. in Shanghai of China, and dynamic response data are collected from the grid-connection terminal of the energy storage system. Next, multidimensional trajectory feature analysis is performed on the measured response data to extract features that are sensitive to the control parameters. A mapping relationship between parameters and these features is then constructed, forming the basis for the optimization objective function. Subsequently, a hybrid optimization strategy is designed by integrating an improved particle swarm optimization (PSO) algorithm with adaptive gradient descent, enabling the nonlinear inversion of the control parameters. Lastly, a simulation verification model is developed in the Bonneville Power Administration Simulation Software (BPA) 5.0 version environment to validate the identified parameters and evaluate the accuracy of the identification through error calculation.

2. A Voltage Ride-Through (VRT) Control Model for Energy Storage Systems

The energy conversion process of a battery energy storage system (BESS) involves bidirectional transformation between chemical and electrical energy. The energy storage medium generates direct current (DC) through electrochemical reactions, which is subsequently converted to alternating current (AC) via power electronic conversion devices for grid integration. The system's dynamic response characteristics are primarily governed by the grid-connected converter and its control system, operating at the electromechanical transient timescale.

The grid-connected converter, serving as the interface between the BESS and the power grid, typically employs a voltage source converter (VSC). Advanced control algorithms enable precise regulation of bidirectional power flow between grid dispatching commands and energy storage units. Figure 1 illustrates the equivalent circuit of the grid-connected converter in a BESS, where U_{dc} : DC-link voltage; I_{dc} : DC-link current; L : equivalent inductance; R : equivalent resistance; E : converter-side AC voltage; U : grid-side AC voltage.

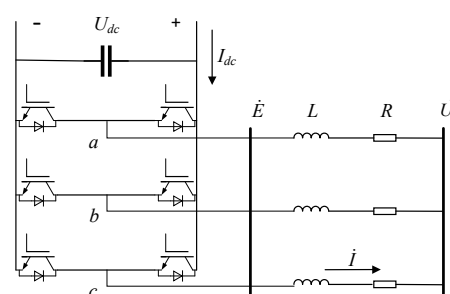


Figure 1. Equivalent circuit diagram of a grid-connected converter for energy storage systems.

As illustrated in Figure 1, the grid-connected converter of the energy storage system can be represented in the dq0 coordinate system as follows:

$$\begin{bmatrix} U_d \\ U_q \end{bmatrix} = - \begin{bmatrix} R + Ls & -\omega L \\ \omega L & R + Ls \end{bmatrix} \begin{bmatrix} i_d \\ i_q \end{bmatrix} + \begin{bmatrix} E_d \\ E_q \end{bmatrix} \quad (1)$$

$$\begin{cases} E_d = \left(\frac{K_{il}}{s} + K_{ip} \right) (i_{rd}^* - i_d) - \omega L i_q + U_d \\ E_q = \left(\frac{K_{il}}{s} + K_{ip} \right) (i_{rq}^* - i_q) + \omega L i_d + U_q \end{cases} \quad (2)$$

In the equations, E_d and E_q : converter-side AC voltage components in the d-axis and q-axis, respectively, U_d and U_q : grid-side AC voltage components in the d-axis and q-axis, respectively, and ω : grid frequency.

The control strategy for grid-connected converters in energy storage systems typically employs a dual-loop coordinated control framework. The outer-loop control, with voltage signals as inputs, generates current reference values through predefined control strategies. The inner-loop control utilizes real-time current measurements as inputs, aiming to track the reference values provided by the outer loop. By leveraging decoupling control algorithms (e.g., dq-axis feedforward decoupling) and converter hardware devices, the inner loop achieves precise current tracking, thereby ensuring the stable output of grid-connected currents. Figure 2 illustrates the mathematical model of the grid-connected converter control for the energy storage system. The main variables are defined as follows: P_r^* , Q_r^* : active power reference and reactive power reference; I_{rd}^* , I_{rq}^* : d-axis and q-axis current component references; I_{dHVRT}^* , I_{qHVRT}^* , I_{dLVRT}^* , I_{qLVRT}^* : reference values for d-axis and q-axis current components during voltage ride-through (VRT) events; I_{1d} , I_{1q} : measured d-axis and q-axis current components; U_{1d} , U_{1q} : d-axis and q-axis components of the AC-side voltage at the grid-connected converter; U_{cd} , U_{cq} : intermediate voltage variables in the control loop; and I_d , I_q : d-axis and q-axis components of the grid-connected converter AC.

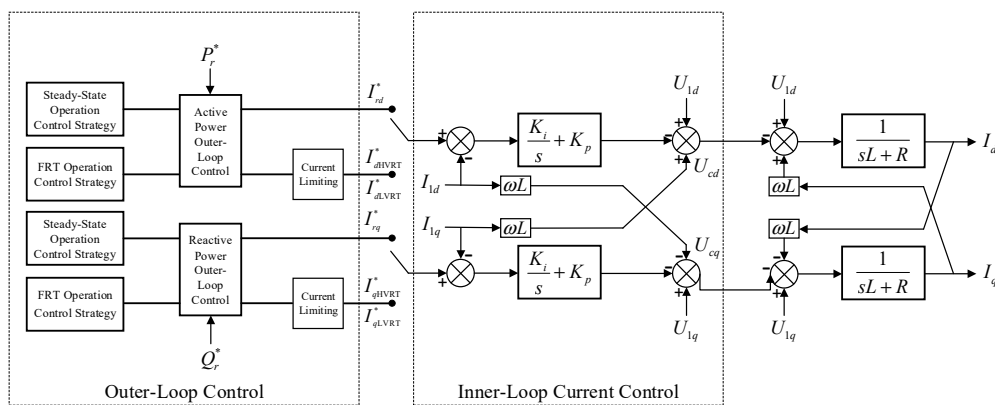


Figure 2. Mathematical model of grid-connected converter control for energy storage systems.

In practical engineering applications, feedforward compensation is commonly adopted to eliminate cross-coupling effects. By combining Equations (1) and (2), the inner-loop current control depicted in Figure 2 can be simplified to the following:

$$\begin{cases} i_d = \frac{1}{Ls+R} \left(\frac{K_{il}}{s} + K_{ip} \right) (i_{rd}^* - i_d) \\ i_q = \frac{1}{Ls+R} \left(\frac{K_{il}}{s} + K_{ip} \right) (i_{rq}^* - i_q) \end{cases} \quad (3)$$

$$\begin{cases} u_{rd}^* = u_{1d} + u_{cd} - \left(\frac{K_{il}}{s} + K_{ip} \right) (i_{rd}^* - i_d) \\ u_{rq}^* = u_{1q} - u_{cq} - \left(\frac{K_{il}}{s} + K_{ip} \right) (i_{rq}^* - i_q) \end{cases} \quad (4)$$

In the above equations: K_{il} , K_{ip} : integral and proportional coefficients of the dq-axis current inner-loop control.

Under steady-state operation, the active power outer-loop control and reactive power outer-loop control can be expressed as follows:

$$\begin{cases} i_{rd}^* = \left(\frac{K_{i_lp}}{s} + K_{p_lp} \right) (P_r^* - P_e) \\ i_{rq}^* = \left(\frac{K_{i_lq}}{s} + K_{p_lq} \right) (Q_r^* - Q_e) \end{cases} \quad (5)$$

In the above equations: K_{p_lp} , K_{i_lp} : proportional and integral coefficients of the active power outer-loop control; K_{p_lq} , K_{i_lq} : proportional and integral coefficients of the reactive power outer-loop control; P_r^* , Q_r^* : active power reference and reactive power reference; and P_e , Q_e : actual active power and actual reactive power.

When grid voltage dip faults occur, the grid-connected converter of the ESS must comply with the HVRT/LVRT requirements specified in the Chinese Standard Technical Requirements for Power Conversion System of Electrochemical Energy Storage System [23].

Under normal grid conditions, the energy storage system typically adopts a dual-loop control framework. The outer-loop control operates in active/reactive power (PQ) mode, adjusting the active power reference (P_r^*) and reactive power reference (Q_r^*); the inner-loop control employs dq-axis decoupled current control via a voltage source converter (VSC) to track the outer-loop references, thereby outputting the desired currents. This architecture prioritizes meeting power dispatch requirements while dynamically responding to fluctuations in grid frequency and voltage.

When grid voltage faults, such as dips or swells, are detected, the outer-loop control switches from PQ mode to a voltage/current-coordinated control mode, prioritizing grid voltage support. A fault-specific current control strategy dynamically generates reactive current references based on voltage deviations, effectively mitigating voltage collapse. Concurrently, the inner-loop current control imposes saturation limits to restrict output currents within the converter's rated capacity, preventing hardware damage. The fault-period current reference equations are defined as follows:

$$\begin{cases} i_{qLVRT}^* = K_1(0.85 - U_t)I_N \\ i_{dLVRT}^* = \min(i_{rd}^*, \sqrt{I_{\max}^2 - i_{qLVRT}^{*2}}) \\ i_{qHVRT}^* = K_2(U_t - 1.15)I_N \\ i_{dHVRT}^* = \min(i_{rd}^*, \sqrt{I_{\max}^2 - i_{qHVRT}^{*2}}) \end{cases} \quad (6)$$

In the equations i_{dHVRT}^* , i_{qHVRT}^* , i_{dLVRT}^* , i_{qLVRT}^* , d-axis and q-axis refer to currents under HVRT conditions and d-axis and q-axis refer to currents under LVRT conditions; K_1 , K_2 : reactive power support coefficient; I_N : rated output current value of the AC terminal; and U_t : ratio of the actual AC terminal voltage to its rated voltage.

$$\begin{cases} u_{1q} = \left(\frac{K_{il}}{s} + K_{ip}\right)(i_{rd}^* - i_d) + u_{rd}^* - u_{cd} \\ u_{1q} = \left(\frac{K_{il}}{s} + K_{ip}\right)(i_{rq}^* - i_q) + u_{rq}^* + u_{cq} \end{cases} \quad (7)$$

3. Parameter Identification Method Based on Dynamic Trajectory Feature Extraction and Hybrid Optimization

The parameter identification method, based on dynamic trajectory feature extraction and hybrid optimization, leverages critical trajectory features extracted from system dynamic response data to construct a parameter sensitivity model, effectively mitigating interference from redundant information. By synergistically integrating global optimization algorithms (e.g., particle swarm optimization) with local gradient-based optimization, this approach achieves multi-stage parameter space exploration, combining broad search capabilities with fine-tuning precision to robustly and efficiently identify unknown parameters in complex nonlinear systems. This methodology strikes a balance between computational efficiency and identification accuracy, making it particularly suitable for model calibration in strongly coupled, multi-variable scenarios.

The identification of FRT control parameters in energy storage systems can thus be formulated as a high-dimensional nonlinear optimization problem:

3.1. Data Preprocessing and Trajectory Segmentation

1. Input Data Normalization

To enhance identification speed and accuracy during parameter identification, the three-phase voltage and current at the grid connection point are normalized using the per-unit system:

$$U_{p.u.} = \frac{U_{abc}}{U_{base}}, I_{p.u.} = \frac{I_{abc}}{I_{base}}, S_{base} = \sqrt{P^2 + Q^2} \quad (8)$$

In the above equations, the base values are defined as $U_{base} = 1.0 \text{ p.u.}$, $I_{base} = S_{base} / \sqrt{3}U_{base}$.

2. Coordinate Transformation and Sequence Component Decomposition

The three-phase voltage parameters are transformed into the synchronous rotating reference frame ($dq0$) via the Park transformation:

$$\begin{bmatrix} U_d \\ U_q \end{bmatrix} = \frac{2}{3} \begin{bmatrix} -\sin \theta & -\sin(\theta - 120^\circ) & -\sin(\theta + 120^\circ) \\ \cos \theta & \cos(\theta - 120^\circ) & \cos(\theta + 120^\circ) \end{bmatrix} \begin{bmatrix} U_a \\ U_b \\ U_c \end{bmatrix} \quad (9)$$

where θ is the grid phase angle tracked in real-time by a phase-locked loop (PLL).

In addition, the three-phase voltage parameters are decomposed into positive-, negative-, and zero-sequence components to analyze asymmetrical grid faults:

$$\begin{bmatrix} U_0 \\ U_1 \\ U_2 \end{bmatrix} = \frac{1}{3} \begin{bmatrix} 1 & 1 & 1 \\ 1 & \alpha & \alpha^2 \\ 1 & \alpha^2 & \alpha \end{bmatrix} \begin{bmatrix} U_a \\ U_b \\ U_c \end{bmatrix}, \alpha = e^{j120^\circ} \quad (10)$$

3. Dynamic Trajectory Window Segmentation

Based on the Chinese Standard *Test Procedure for Power Conversion Systems of Electrochemical Energy Storage Systems* [24], the time window thresholds are determined based on the control loop time constants of the energy storage system. The trajectory segmentation is defined as follows:

- Transient Window ($t_0 \sim t_0 + 100 \text{ ms}$): This window captures nonlinear dynamics during fault inception.
- Transition Window ($t_0 + 100 \text{ ms} \sim t_0 + 300 \text{ ms}$): This window analyzes the parameter adjustment process of the control loops.
- Steady-State Window ($t_0 + 300 \text{ ms} \sim t_1$): This window evaluates long-term stability and harmonic characteristics post-fault.

3.2. Dynamic Trajectory Feature Extraction

To achieve precise identification of control parameters, key electrical response data are analyzed, from which the most sensitive feature indicators are selected as the core components of the optimization objective function.

1. Positive Sequence Voltage Feature

The voltage recovery time is selected as a characteristic, defined as the time required for the voltage to rise from the fault point to 90% of the steady-state value.

$$T_{\text{rise}} = t(U_1 = 0.9U_n) - t_{\text{fault}} \quad (11)$$

Its features are used to measure the response speed of the voltage loop PI controller and the reactive power support mechanism.

2. Active Power Feature

The power fluctuation rate is extracted to reflect the controller's active regulation capability during the early stages of the fault.

$$R_P = \max \left| \frac{dP(t)}{dt} \right|_{t \in [t_0, t_0 + 100\text{ms}]} \quad (12)$$

This feature is used to assess the response ability of the active power reference regulation loop to sudden disturbances.

3. Reactive Power Feature

The reactive power response delay time represents the action response time of the HVRT/LVRT controller.

$$\Delta T_q = t(I_q > \gamma I_{q,ss}) - t_{\text{fault}} \quad (13)$$

In the equation, $I_{q,ss}$ represents the steady-state value of the reactive current. The parameter γ is an empirical proportional coefficient, typically set in the range of 0.05 to 0.10, representing the effective response when the deviation from the reference value exceeds 5% to 10%. This feature reflects the delay time in initiating reactive power support by the HVRT/LVRT control logic.

4. Active Current Feature

The overshoot amount of current is extracted to characterize the control precision and stability of the d-axis current loop.

$$\Delta I_{d,over} = \max I_d(t) - I_{d,ss} \quad (14)$$

In the equation, $I_{d,ss}$ represents the steady-state value of the active current. This feature is used to evaluate the transient overshoot phenomenon in the current inner loop PI regulation process.

5. Reactive Current Feature

The initial slope is selected to evaluate the reactive power support capability in the early stage of voltage disturbance.

$$S_{I_q} = \frac{I_q(t_2) - I_q(t_1)}{t_2 - t_1}, \quad t_1 = t_{\text{fault}}, \quad t_2 = t_1 + 20 \text{ ms} \quad (15)$$

The initial response slope is closely related to the reactive power support coefficients K_1 and K_2 .

6. Power Tracking Error

The active and reactive power error is used to regulate the accuracy of the PQ controller.

$$\text{MSE}_{P,Q} = \frac{1}{T} \int_{t_0}^{t_0+T} \left(P, Q^{\text{sim}}(t) - P, Q^{\text{meas}}(t) \right)^2 dt \quad (16)$$

Total Harmonic Distortion (THD)

To account for the waveform quality during steady-state operation, the Total Harmonic Distortion (THD) is introduced as a penalty term. It is defined as follows:

$$\text{THD}_i = \frac{\sqrt{\sum_{h=2}^{50} U_h^2}}{U_1} \quad (17)$$

where U_h represents the RMS value of the h-th harmonic.

3.3. Hybrid Optimization Algorithm Design

3.3.1. Establish the Objective Function

The control parameters listed in Table 1 are defined as the primary identification target.

Table 1. Key Parameters of the Energy Storage Converter.

Parameter Category	Parameter Name
Active Power Setpoint	P_r^*
Reactive Power Setpoint	Q_r^*
Reactive Power Support Coefficient	K_1, K_2
Power Loop Parameters	$K_{p_lp}, K_{i_lp}, K_{p_lq}, K_{i_lq}$
Current Loop Parameters	K_{iL}, K_{iP}
Grid-side Maximum Current	I_{max}

$$\theta = \left[K_{p_lp}, K_{i_lp}, K_{p_lq}, K_{i_lq}, K_{iL}, K_{iP}, K_1, K_2, I_{max} \right]^T \quad (18)$$

The sensitivity analysis of these six features is performed using the Sobol index method to select control parameters that have a significant impact during energy storage voltage faults. Based on the actual hardware limitations of the controller, a parameter search space is established. The optimized objective function is then formulated as follows:

$$J(\theta) = \sum_{i=1}^5 \alpha_i \cdot \left(f_i^{\text{sim}} - f_i^{\text{meas}} \right)^2 + \alpha_{P,Q} \text{MSE}_{P,Q} + \beta \text{THD} \quad (19)$$

where α represents the importance of each indicator in the optimization objective, with higher α values indicating greater importance. f_i^{sim} denotes the value of each feature obtained from simulation data, while f_i^{meas} represents the value derived from measured data. β is the weighting factor for the THD term.

3.3.2. Global Optimization Phase

The Particle Swarm Optimization (PSO) algorithm is employed for global search. The state update formula for particle i at iteration t is as follows:

$$\begin{cases} v_i^{(t+1)} = \omega \times v_i^{(t)} + c_1 r_1 \left(p_{best,i}^{(t)} - \theta_i^{(t)} \right) + c_2 r_2 \left(g_{best}^{(t)} - \theta_i^{(t)} \right) \\ \theta_i^{(t+1)} = \theta_i^{(t)} + v_i^{(t+1)} \end{cases} \quad (20)$$

In the equations, ω : inertia weight; c_1, c_2 : learning factors; $r_1, r_2 \sim U(0, 1)$: random numbers; $p_{best,i}$: historical best position of particle i ; g_{best} : global best position.

Out-of-bound parameters are handled via reflective boundary conditions:

$$\theta_{i,j}^{(t+1)} = \begin{cases} 2 \cdot \theta_{\min,j} - \theta_{i,j}^{(t+1)}, & \text{if } \theta_{i,j}^{(t+1)} < \theta_{\min,j} \\ 2 \cdot \theta_{\max,j} - \theta_{i,j}^{(t+1)}, & \text{if } \theta_{i,j}^{(t+1)} > \theta_{\max,j} \\ \theta_{i,j}^{(t+1)}, & \text{otherwise} \end{cases} \quad (21)$$

3.3.3. Local Optimization Phase

The objective function is decomposed into differentiable (feature error) and non-differentiable (THD) components:

$$J(\theta) = \underbrace{\sum_{i=1}^5 \alpha_i \cdot (f_i^{\text{sim}} - f_i^{\text{meas}})^2}_{J_{\text{smooth}}(\theta)} + \alpha_{P,Q} \text{MSE}_{P,Q} + \underbrace{\beta \text{THD}}_{J_{\text{non-smooth}}(\theta)} \quad (22)$$

The Levenberg–Marquardt (LM) algorithm optimizes the differentiable part, and the THD term is indirectly optimized via weight constraints β THD.

The residual vector is defined as follows:

$\mathbf{r}(\theta) = [\sqrt{\alpha_1}(f_1^{\text{sim}} - f_1^{\text{meas}}), \dots, \sqrt{\alpha_5}(f_5^{\text{sim}} - f_5^{\text{meas}}), \sqrt{\alpha_{P,Q}}\text{MSE}_{P,Q}]^T$ with the Jacobian matrix:

$$\mathbf{J}_r(\theta) = \begin{bmatrix} \frac{\partial r_1}{\partial \theta_1} & \cdots & \frac{\partial r_1}{\partial \theta_j} \\ \vdots & \ddots & \vdots \\ \frac{\partial r_{P,Q}}{\partial \theta_1} & \cdots & \frac{\partial r_{P,Q}}{\partial \theta_j} \end{bmatrix} \quad (23)$$

In the equation, the partial derivative $\frac{\partial r_i}{\partial \theta_j} = \sqrt{\alpha_i} \cdot \frac{\partial f_i^{\text{sim}}}{\partial \theta_j}$ is computed via the finite difference method or adjoint equations.

The Levenberg–Marquardt (LM) algorithm combines gradient descent and the Gauss–Newton method, with its iteration formula expressed as follows:

$$\theta^{(k+1)} = \theta^{(k)} - (\mathbf{J}_r^T \mathbf{J}_r + \lambda \mathbf{I})^{-1} \mathbf{J}_r^T \mathbf{r} \quad (24)$$

where λ is a dynamically adjusted damping factor:

$$\lambda^{(k+1)} = \begin{cases} \lambda^{(k)} / 10, & \text{if } J_{\text{smooth}}(\theta^{(k+1)}) < J_{\text{smooth}}(\theta^{(k)}) \\ \lambda^{(k)} \times 10, & \text{otherwise} \end{cases} \quad (25)$$

3.3.4. Hybrid Optimization Strategy

Multiple candidate solutions from the PSO population undergo LM local optimization when either condition is met:

1. Convergence stagnation: Convergence stagnation is triggered when the global best solution (e.g., g_{best} in PSO) exhibits no significant improvement in its objective function value $J(g_{\text{best}})$ over stagnation for consecutive iterations.
2. Relative error threshold:

$$\frac{|J(g_{\text{best}}^{(t)}) - J(g_{\text{best}}^{(t-T)})|}{|J(g_{\text{best}}^{(t-T)})|} < \epsilon_{\text{rel}} \quad (26)$$

The dynamic trajectory feature extraction and PSO-LM hybrid optimization method effectively mitigates the entrapment in local optima that occurs in traditional PSO, enhances identification accuracy, and improves engineering applicability. Integrating Kriging surrogate models further reduces computational costs and complexity, making it suitable for simulation-intensive complex systems.

4. Discussion: Identification Data and Algorithm Flow

4.1. Measured Identification Data and Operating Condition Confirmation

Based on the Chinese Standard Test Procedure for Power Conversion Systems of Electrochemical Energy Storage Systems [24–26], HVRT/LVRT tests were conducted on the energy storage system using a voltage fault generator as shown in Figure 3. The tests comprise at least five voltage dip points, including 0%Un and 20%Un, with the remaining points distributed across the ranges of 30%Un–50%Un, 50%Un–70%Un, and 70%Un–90%Un. In addition, three voltage swell points were selected, including 130%Un, with the other two located within the ranges of 110%Un–120%Un and 120%Un–125%Un.

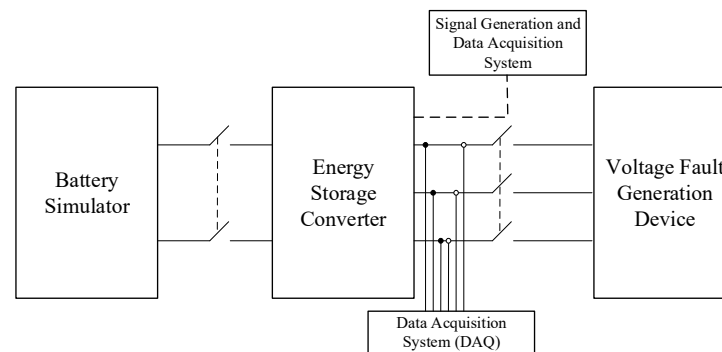


Figure 3. FRT test diagram.

During HVRT/LVRT tests, the primary electrical parameters measured at the grid connection point include three-phase voltage, active power, reactive power, active current, and reactive current. These parameters were analyzed to derive the control parameters (e.g., PI gains and current limits) and fault ride-through control parameters of the grid-connected converter. In this paper, we focus on parameter identification during voltage dips and swells under charging mode. A fault ride-through test model was developed in the MT 6040 Simulator using the identified control parameters. Simulations under identical operating conditions as the field tests were performed, recording positive-sequence voltage, active/reactive power, and active/reactive current waveform for comparison with measured data.

4.2. Parameter Identification Flow for Voltage Ride-Through Models

To accurately identify transient control parameters for voltage ride-through and enhance the practicality of the algorithm, a dynamic trajectory feature extraction and PSO-LM hybrid optimization method is proposed. The parameter identification flow is illustrated in Figure 4, with the following steps:

1. **Model Setup and Data Preprocessing:** Establish a voltage ride-through model for the energy storage system, define control parameters for identification, and preprocess measured data to extract trajectory features as shown in Table 2.
2. **Objective Function Construction:** Formulate an objective function linking measured data and control parameters. Initialize particle positions in PSO with parameter candidates.
3. **Global Optimization (PSO):** Update particle positions and velocities until the global convergence criteria are met. Use dynamic trajectory features to determine whether to switch to local optimization.
4. **Local Optimization (LM):** Apply the Levenberg–Marquardt (LM) algorithm to refine parameters until convergence. Output the final identified control parameters.

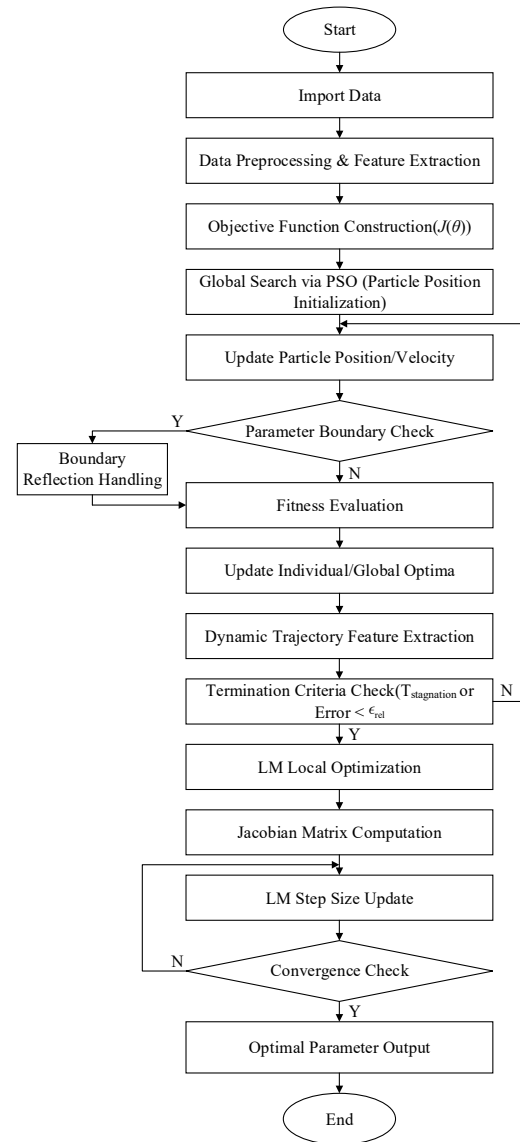


Figure 4. Parameter identification process.

Table 2. Voltage fault scenarios.

Voltage Magnitude (p.u.)	Voltage Dip Duration (ms)
0	100~150
0.20	600~700
0.50	1100~1300
1.20	9800~10,100
1.25	970~1020
1.30	450~550

5. Simulation Case Analysis

5.1. Simulation Conditions

The hardware-in-the-loop (HIL) testing system for the energy storage controller, built on the MT 6040 Simulator platform, is shown in Figure 5. Real-time simulation is used to collect measured data, including positive-sequence voltage, active and reactive power, and active and reactive current at the ESS grid-connected inverter port, for analysis.

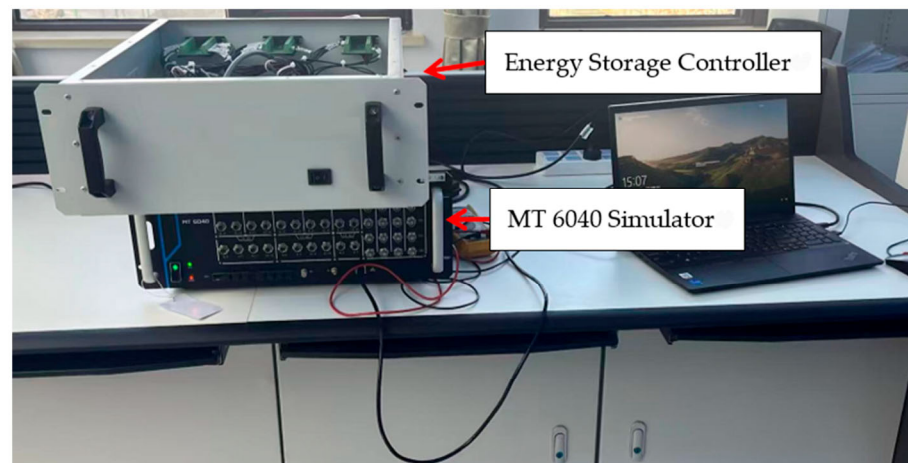


Figure 5. The HIL testing system for the energy storage controller was built on the MT 6040 Simulator platform.

The hardware-in-the-loop (HIL) testing system for the energy storage controller, built on the MT 6040 Simulator platform, is shown in Figure 5. Real-time simulation was used to collect measured data, including positive-sequence voltage, active and reactive power, and active and reactive current at the ESS grid-connected inverter port, for analysis.

To validate the effectiveness and accuracy of the proposed parameter identification method, a fault ride-through test model for the energy storage system was established using the BPA. The model employs the identified voltage fault ride-through control strategy to regulate system behavior. The energy storage system described in this study has a rated capacity of $3.76 \text{ MV} \cdot \text{A}$ and a rated voltage of 35 kV, connected via a step-up transformer to a 220 kV transmission line and an infinite bus system.

Voltage faults are applied at the 35 kV bus to replicate measured voltage deviations at the grid connection point. Simulation data, including three-phase voltages, active power, reactive power, active current, and reactive current, were recorded. To verify the validity of the identification results, a subset of operating conditions was used as the experimental group for parameter identification. In contrast, the remaining conditions serve as the validation group to test the correctness of the identified parameters.

5.2. Symmetrical Case Validation

To verify the accuracy of the parameter identification results obtained using the proposed algorithm, we conducted experiments under both charging and discharging modes. Symmetrical conditions with high (FP), medium (MP), and small power (SP) levels were tested, where voltage sags to $0\%U_n$ and $50\%U_n$ and swells to $130\%U_n$ were used as the identification experiment group. For the validation of LVRT, a symmetrical FP condition with a voltage sag to $20\%U_n$ was selected under both charging and discharging modes. To further evaluate multi-condition adaptability, HVRT validation was performed using symmetrical FP conditions with voltage swell to $125\%U_n$ under charging mode and $120\%U_n$ under discharging mode. The parameter identification results under symmetrical conditions are listed in Tables 3–7, and their comparison with the measured data are shown in Figures 6–9.

5.2.1. LVRT

The parameter identification results under symmetrical conditions of LVRT and their comparison with the measured data from MT6040 are shown in Figures 6 and 7.

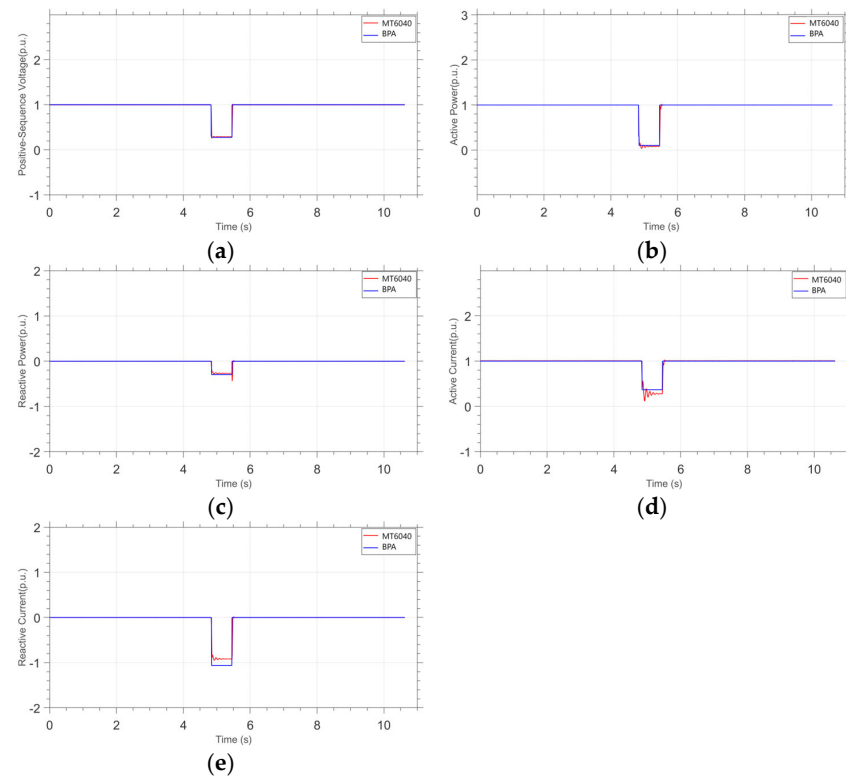


Figure 6. CH: comparison of simulated and measured results for symmetrical HP voltage sag to 20%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

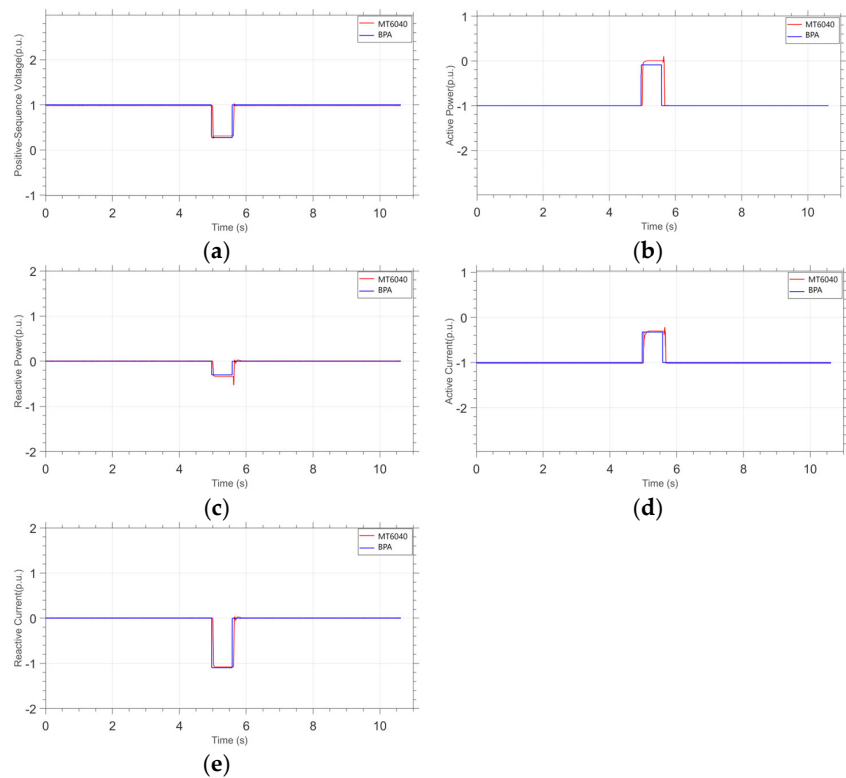


Figure 7. DH: comparison of simulated and measured results for symmetrical HP voltage sag to 20%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

5.2.2. HVRT

The parameter identification results under symmetrical conditions of HVRT and their comparison with the measured data form MT6040 are shown in Figures 8 and 9.

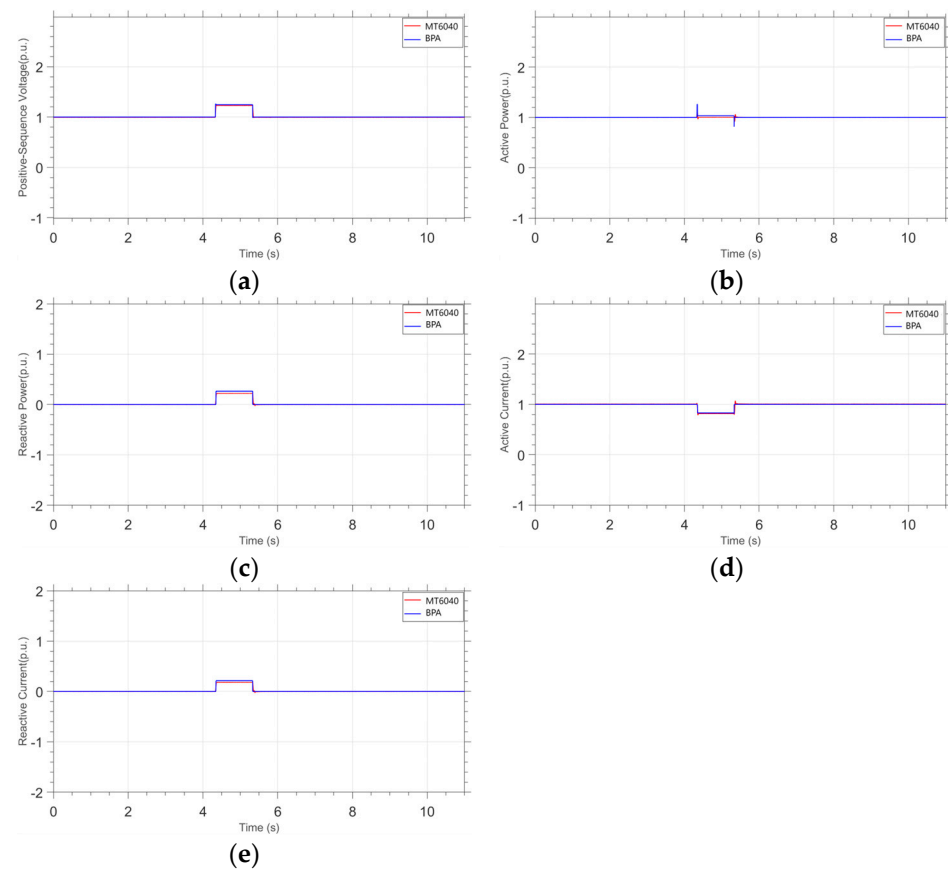


Figure 8. CH: comparison of simulated and measured results for symmetrical HP voltage swell to 125%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

The Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under symmetrical conditions of LVRT and HVRT are listed in Tables 3–7.

Table 3. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under symmetrical conditions.

Conditions		ΔU	ΔP	ΔQ	ΔI_P	ΔI_Q
LVRT	CH 20%Un	1.04%	1.27%	1.63%	1.72%	1.84%
	DH 20%Un	1.12%	1.76%	1.64%	1.70%	1.53%
HVRT	CH 125%Un	1.02%	1.07%	1.17%	1.03%	1.08%
	DH 120%Un	1.12%	1.01%	1.11%	1.02%	1.12%

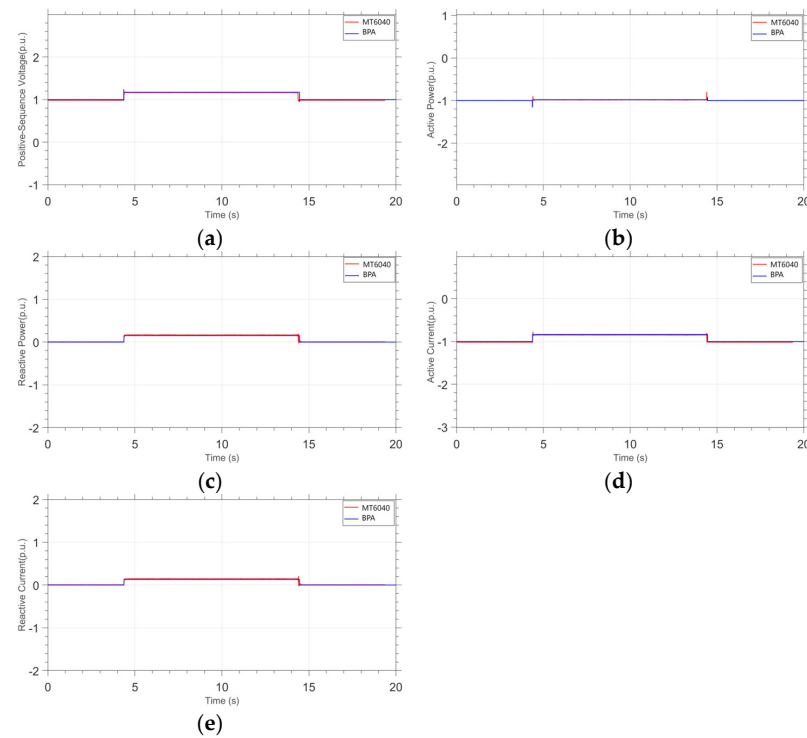


Figure 9. DH: comparison of simulated and measured results for symmetrical HP voltage swell to 120%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

Table 4. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under symmetrical conditions (CH FP20%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.30%	0.21%	0.23%	0.52%	0.39%
Transient during fault	1.27%	1.16%	1.32%	1.93%	1.54%
Steady-state during fault	1.07%	1.83%	2.14%	3.41%	3.97%
Post-fault transient	1.22%	2.01%	2.54%	2.61%	1.74%
Post-fault steady-state	0.30%	0.33%	0.32%	0.59%	0.42%

Table 5. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under symmetrical conditions (DH FP20%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.45%	0.20%	0.53%	0.52%	0.44%
Transient during fault	1.17%	2.06%	1.82%	1.93%	1.54%
Steady-state during fault	1.07%	2.73%	2.04%	2.59%	1.97%
Post-fault transient	1.24%	3.11%	2.75%	3.35%	2.44%
Post-fault steady-state	0.31%	0.33%	0.62%	0.59%	0.52%

Table 6. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under symmetrical conditions (CH FP125%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.25%	0.28%	0.25%	0.31%	0.31%
Transient during fault	0.92%	1.64%	1.14%	1.21%	1.24%
Steady-state during fault	1.51%	1.72%	2.09%	1.91%	1.88%
Post-fault transient	0.96%	1.99%	1.22%	1.56%	1.32%
Post-fault steady-state	0.30%	0.32%	0.24%	0.49%	0.42%

Table 7. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under symmetrical conditions (DH FP125%Un).

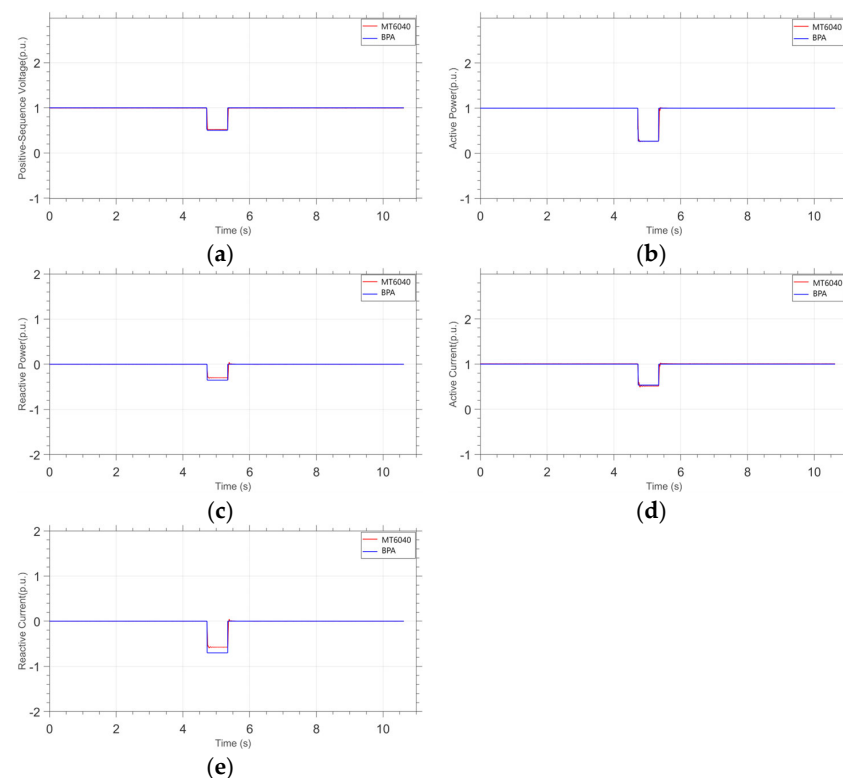
Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.75%	0.31%	0.55%	0.81%	0.81%
Transient during fault	1.12%	1.64%	1.14%	1.01%	1.24%
Steady-state during fault	0.71%	1.12%	2.09%	1.21%	1.98%
Post-fault transient	1.09%	1.79%	1.72%	1.36%	2.02%
Post-fault steady-state	0.90%	0.39%	0.54%	0.79%	0.42%

5.3. Validation of Asymmetrical Case Identification Results

In the actual operating conditions of energy storage systems, it is essential to consider not only symmetrical faults but also asymmetrical faults. In this section, we describe identification experiments conducted under FP, MP, and SP levels in both charging and discharging modes, where voltage sags to 0%Un and 50%Un and swells to 130%Un are applied. For LVRT validation, an asymmetrical FP condition with a voltage sag to 20%Un was tested under both charging and discharging modes. To verify identification accuracy under diverse scenarios, HVRT validation was performed using asymmetrical FP conditions with a voltage swell to 125%Un under charging mode and 120%Un under discharging mode. The parameter identification results for asymmetrical scenarios are listed in Tables 8–12 and compared with the measured data in Figures 10–13.

5.3.1. LVRT

The parameter identification results under asymmetrical conditions of LVRT and their comparison with the measured data from MT6040 are shown in Figures 10 and 11.

**Figure 10.** CH: comparison of simulated and measured results for asymmetrical HP voltage sag to 20%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

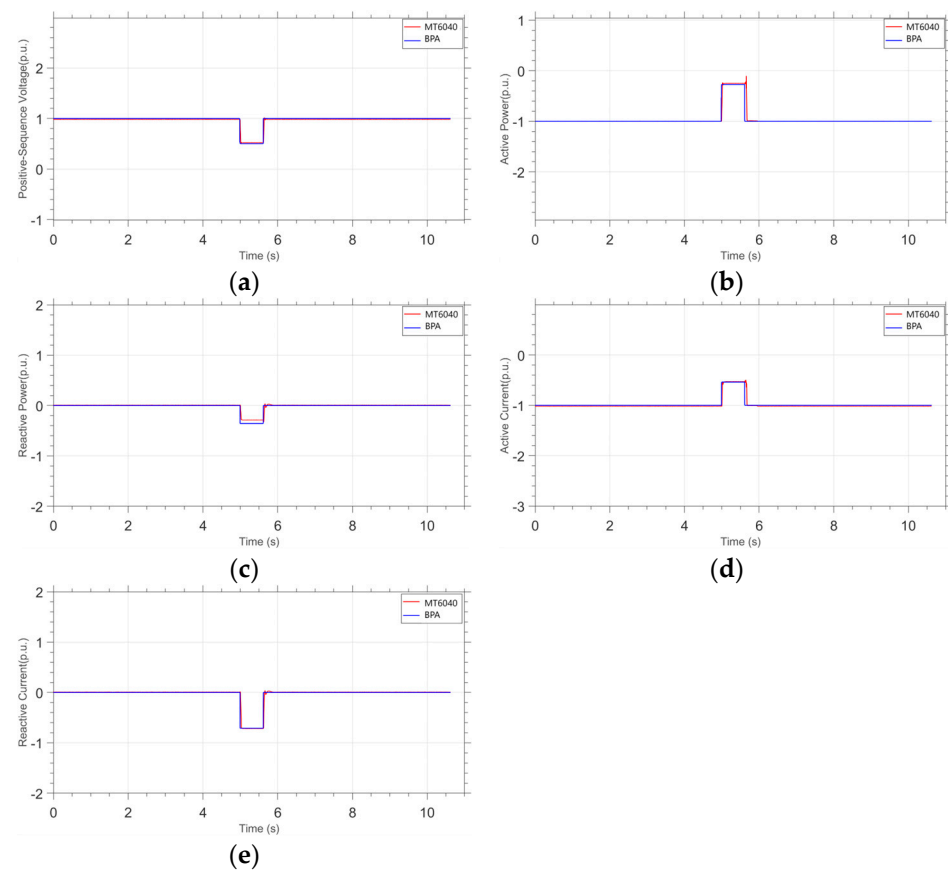


Figure 11. DH: comparison of simulated and measured results for asymmetrical HP voltage sag to 20%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

5.3.2. HVRT

The parameter identification results under asymmetrical conditions of LVRT and their comparison with the measured data from MT6040 are shown in Figures 12 and 13.

The Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under asymmetrical conditions of LVRT and HVRT are listed in Tables 3–7.

Table 8. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under asymmetrical conditions.

Conditions		ΔU	ΔP	ΔQ	ΔI_P	ΔI_Q
LVRT	CH 20%Un	0.96%	0.88%	1.63%	1.52%	1.74%
	DH 20%Un	0.99%	1.01%	1.22%	1.56%	1.39%
HVRT	CH 125%Un	0.99%	0.77%	1.07%	1.53%	0.88%
	DH 120%Un	1.21%	1.06%	1.52%	1.89%	1.59%

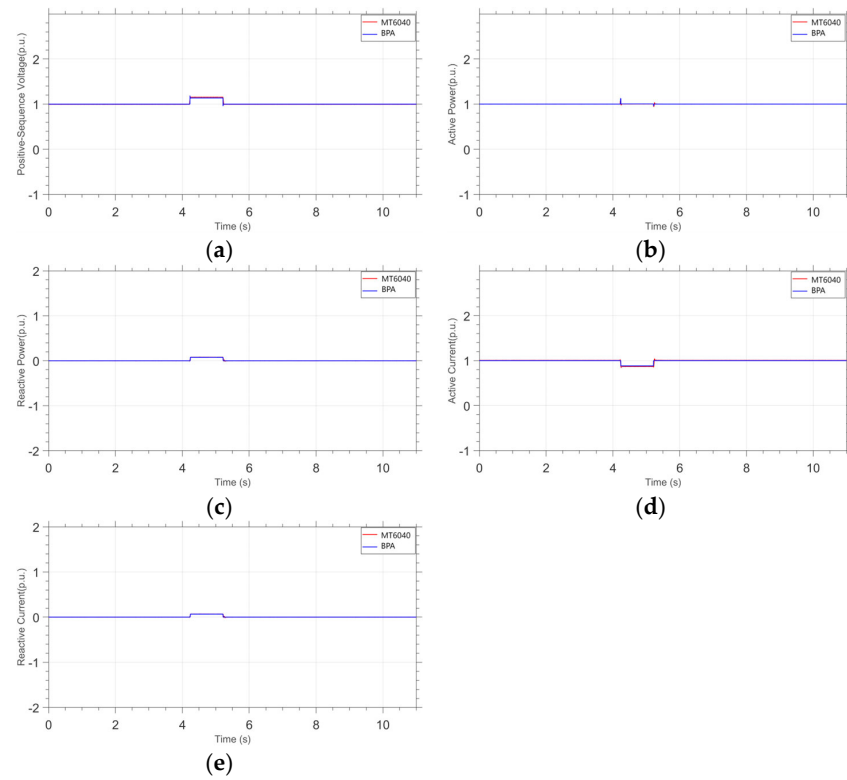


Figure 12. CH: comparison of simulated and measured results for asymmetrical HP voltage swell to 125%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

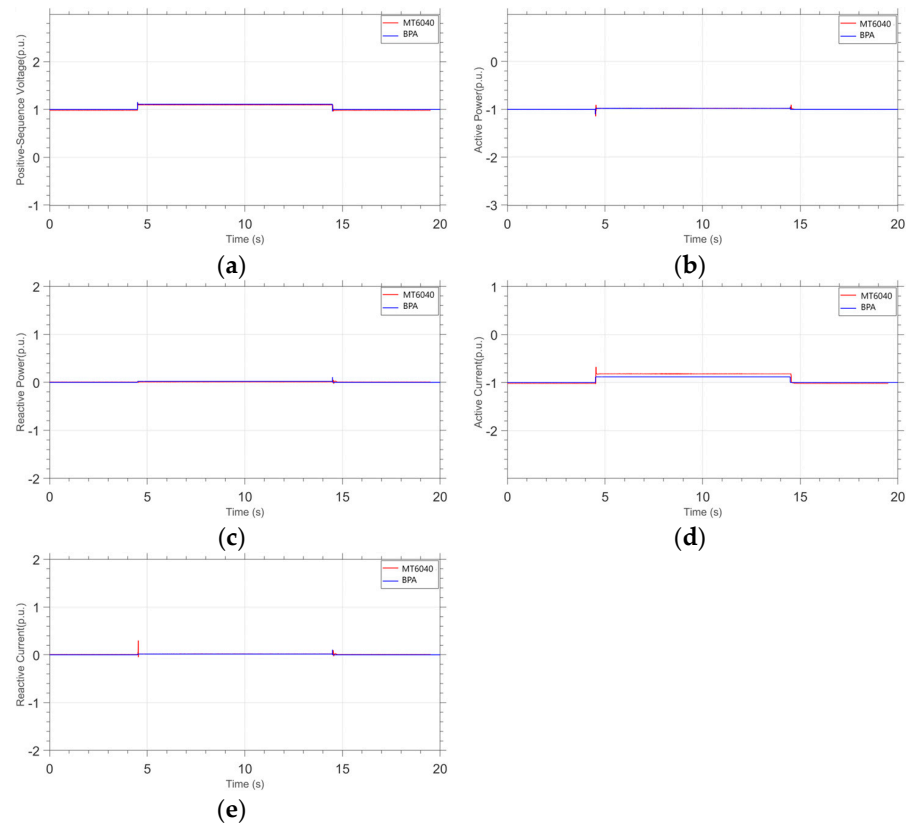


Figure 13. DH: comparison of simulated and measured results for asymmetrical HP voltage swell to 120%Un: (a) positive-sequence voltage; (b) active power; (c) reactive power; (d) active current; (e) reactive current.

Table 9. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under asymmetrical conditions (CH FP20%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.26%	0.21%	0.23%	0.52%	0.31%
Transient during fault	1.07%	1.06%	1.72%	1.13%	1.54%
Steady-state during fault	1.17%	1.03%	2.14%	1.91%	2.97%
Post-fault transient	1.02%	1.11%	2.54%	1.31%	1.74%
Post-fault steady-state	0.30%	0.31%	0.62%	0.51%	0.32%

Table 10. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under asymmetrical conditions (DH FP20%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.75%	0.32%	0.63%	0.82%	0.59%
Transient during fault	1.01%	1.56%	1.22%	1.95%	1.51%
Steady-state during fault	1.02%	1.73%	1.54%	1.11%	1.07%
Post-fault transient	1.04%	2.79%	1.64%	2.02%	1.44%
Post-fault steady-state	0.80%	0.33%	0.71%	0.89%	0.60%

Table 11. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under asymmetrical conditions (CH FP125%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.25%	0.33%	0.25%	0.61%	0.21%
Transient during fault	0.82%	1.04%	0.54%	1.01%	0.84%
Steady-state during fault	1.51%	0.72%	1.09%	1.11%	1.01%
Post-fault transient	1.09%	0.92%	1.02%	1.16%	0.52%
Post-fault steady-state	0.30%	0.28%	0.24%	0.69%	0.22%

Table 12. Comparison of steady-state average error in fault identification by the PSO-LM algorithm identification group under asymmetrical conditions (DH FP125%Un).

Interval	ΔU_{mean}	ΔP_{mean}	ΔQ_{mean}	ΔI_{Pmean}	ΔI_{Qmean}
Pre-fault steady-state	0.85%	0.50%	0.75%	0.91%	0.71%
Transient during fault	1.02%	1.64%	1.54%	2.31%	2.24%
Steady-state during fault	1.11%	0.53%	1.69%	2.41%	0.88%
Post-fault transient	1.09%	1.59%	1.22%	1.76%	1.52%
Post-fault steady-state	0.90%	0.33%	0.74%	1.29%	0.72%

6. Conclusions

In this paper, we propose a non-intrusive parameter identification method based on dynamic trajectory feature extraction and a hybrid optimization algorithm to address the challenges of identifying HVRT/LVRT control parameters for energy storage systems. The main conclusions can be summarized as follows:

1. **Dynamic Trajectory Feature Extraction Mechanism:** By capturing key features corresponding to different dynamic responses, a sensitivity mapping relationship is established between control parameters and dynamic responses. This approach significantly improves the feature matching accuracy under HVRT/LVRT multi-scenario conditions and reduces identification deviations caused by parameter coupling effects.
2. By integrating global search with local refinement, this strategy addresses the issue of local optima in high-dimensional nonlinear parameter spaces. The simulation results

demonstrate that the method achieves parameter identification errors of less than 3.5% across five typical voltage fault scenarios, exhibiting faster convergence and a strong generalization ability across different operating conditions.

3. Measurement-Driven Simulation Validation System: The method was validated through the fault ride-through model developed on the BPA platform, exhibiting key dynamic response metrics (e.g., voltage recovery time and reactive power support accuracy) with errors below 5% compared to field measurements, providing a high-fidelity simulation tool for transient stability assessment in renewable-integrated power systems.

Future research directions will focus on the following:

1. Integrating HIL testing platforms to enhance algorithm robustness in real-time control;
2. Exploring deep learning-physics model fusion methods to improve parameter adaptability under complex fault sequences;
3. Developing universal parameter identification methods applicable to diverse renewable energy devices.

The results of this study provide a critical modeling foundation for energy storage systems to actively support grid stability and offer significant practical value for transient stability control in power systems with high renewable energy penetration.

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