

Article

Dominant-Mode-Based SCR-Adaptive SG-PSO Tuning for LVRT Recovery of PMSG Wind Turbines in Weak Grids

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Abstract

Transient instability during the low-voltage ride-through (LVRT) recovery of permanent magnet synchronous generator (PMSG) wind turbines is strongly influenced by weak-grid interactions, while the quantitative relationship among grid strength, control parameters, and recovery performance remains insufficiently understood. This paper develops a small-signal transient recovery characteristic matrix for a grid-connected PMSG system by incorporating the dynamic interactions among the phase-locked loop (PLL), inner current loop, DC-link voltage loop, and grid-side inductance. Dominant-mode and root-locus analyses are employed to investigate how variations in the short-circuit ratio (SCR) affect dominant eigenvalue trajectories and the sensitivities of six PI control parameters. Based on the identified dynamic mechanisms, an SCR-adaptive sensitivity-guided particle swarm optimization (SG-PSO) method is proposed for coordinated PI parameter tuning. The proposed approach introduces SCR-dependent damping constraints and physical feasibility constraints, while normalized real-part eigenvalue sensitivities are utilized to guide the optimization process toward the most influential control parameters. Comparative simulation results demonstrate that, under SCR = 1.5, SG-PSO reduces the point of common coupling (PCC) voltage overshoot to 1.4% and shortens the recovery time to 58 ms, achieving better transient recovery indices than conventional PSO and OBO-PI under the same simulation and constraint settings. Under SCR = 2.5, the recovery time is further reduced to 46 ms while maintaining a low overshoot of 0.9%. Additional robustness tests under parameter uncertainties and fault-condition variations further support the effectiveness and adaptability of the proposed method. The results indicate that the proposed SG-PSO framework provides an effective solution for enhancing LVRT recovery performance of PMSG wind turbines operating in weak-grid environments.

Keywords: permanent magnet synchronous generator; low-voltage ride-through; weak grid; short-circuit ratio; dominant-mode analysis; transient stability



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1. Introduction

With the continuous increase in wind power penetration, power systems are becoming increasingly dominated by converter-interfaced renewable generation. Although wind power contributes significantly to decarbonization, the reduction in system strength and inertia makes grid operation more sensitive to severe disturbances. Recent studies have further highlighted that voltage control, synchronization stability, and FRT capability are critical issues for renewable-rich power systems [1–3]. Therefore, modern grid codes

require wind turbines not only to remain connected during voltage sags but also to provide dynamic voltage support during and after faults. In this context, the LVRT capability of PMSG wind turbines has become an important factor affecting the secure integration of wind power [1–3].

PMSG wind turbines are usually connected to the grid through back-to-back converters. The grid-side converter is responsible for DC-link voltage regulation, grid-current control, synchronization, and reactive power support. These functions are mainly realized by the DC-link voltage loop, the inner current loop, and the phase-locked loop (PLL). During the LVRT process, the converter control mode changes with the grid voltage condition. In the fault period, reactive current injection is usually required to support the point of common coupling (PCC) voltage, whereas after fault clearance, the system must return to the normal power-tracking mode and restore the DC-link and PCC voltages within a short time. Therefore, the LVRT recovery stage is not only a voltage restoration process but also a strongly coupled transient process involving the PLL, current loop, DC-link voltage loop, and grid impedance. The transient stability of grid-connected converters in wind turbine systems under severe disturbances has also been recognized as a key issue, requiring dedicated analytical methods to characterize post-fault dynamic behavior [4].

A considerable number of studies have investigated LVRT enhancement methods for PMSG wind turbines. Existing methods can generally be classified into external hardware-based methods and control-based methods. External devices, such as braking resistors, energy storage units, crowbar circuits, and reactive compensation devices, can improve FRT performance but usually increase system cost and complexity [2,3]. Control-based methods, including reactive current injection, DC-link voltage control, current limitation, and mode switching strategies, are more economical and flexible for converter-interfaced wind turbines [5–7]. However, most of these methods focus on improving the time-domain LVRT response through predefined control logic, while the quantitative relationship among grid strength, internal control parameters, and post-fault recovery dynamics is still not sufficiently clarified.

The effect of weak-grid conditions on converter stability has also received increasing attention. The short-circuit ratio (SCR) is widely used as an indicator of grid strength, and a lower SCR usually indicates stronger interaction between the converter and grid impedance. Under weak-grid conditions, PCC voltage distortion caused by current perturbations can be transferred to the PLL input, thereby deteriorating synchronization dynamics and reducing system damping. Previous studies have shown that PLL parameters and grid strength have significant impacts on the stability margin of wind power converters [8]. Under extremely weak-grid connections, grid-following converter parameters should be carefully tuned to avoid insufficient damping [9]. In addition, SCR has been widely used to evaluate the influence of network strength on wind turbine stability and control-parameter settings [10]. Therefore, it is necessary to combine SCR-based grid-strength characterization with internal control-loop modeling to analyze the LVRT recovery dynamics of PMSG wind turbines.

Recent research has also shown that dynamic interactions between renewable energy plants and external grid-side systems can significantly affect temporary overvoltage and post-disturbance voltage behavior. For example, temporary overvoltage in LCC-HVDC sending systems with renewable energy plants has been analyzed by partitioning the transient process and examining the dynamic interaction mechanism during commutation-failure-related disturbances [11]. Unlike such system-level overvoltage studies, the present work focuses on the LVRT recovery stage of a grid-connected PMSG wind turbine and establishes a small-signal transient recovery characteristic matrix to quantify how SCR variation affects the coupled dynamics among the PLL, current loop, DC-link voltage loop, and grid-side inductance.

In addition, adaptive PSO, multi-objective PSO, grey wolf optimization, artificial hummingbird optimization, and reinforcement-learning-based or deep-reinforcement-learning-based control strategies have been increasingly explored for converter control, wind-energy systems, and LVRT performance enhancement [12–17]. For example, a hybrid PSO–artificial hummingbird algorithm has been employed to tune STATCOM parameters for improving grid-code compliance in a wind-assisted microgrid [16]. Such hybrid metaheuristic frameworks enhance transient performance mainly by combining different stochastic search mechanisms and coordinating an external reactive-power compensation device. Advanced fuzzy-control-based inertia-support strategies, such as multiple-model type-3 fuzzy control with an Active Rotary Inertia Driver (ARID), have also been developed to enhance offshore wind-turbine stability and inertia support under complex operating conditions [18]. These methods have shown advantages in global search capability, nonlinear control performance, inertia-support enhancement, reactive-power compensation, or data-driven decision-making. However, they generally emphasize time-domain performance improvement, global optimization efficiency, nonlinear rule-based control, auxiliary inertia regulation, external compensation, or control-policy learning, while the physical relationship among grid strength, dominant-mode movement, and controller-parameter sensitivity is still not explicitly embedded into the tuning process. In contrast, the proposed SG-PSO framework does not rely on an additional STATCOM, an auxiliary inertia-support device, or the hybridization of multiple metaheuristic operators. Instead, it tunes the existing PI parameters of the PMSG grid-side converter by embedding SCR-dependent dominant-mode sensitivity and damping-margin constraints into the optimization process. Therefore, the novelty of SG-PSO lies in its physically informed and grid-strength-adaptive PI tuning logic, rather than only in the use of a stochastic optimization algorithm.

Based on the above literature review, two research gaps remain. First, the LVRT recovery process of PMSG wind turbines under weak-grid conditions requires a unified small-signal model that explicitly includes the PLL, inner current loop, DC-link voltage loop, and grid-side inductance so that the relationship between control parameters and dominant recovery modes can be quantified. Second, the PI tuning strategy should not only pursue better time-domain performance but also consider SCR-dependent damping requirements and the sensitivity of dominant eigenvalues to different control parameters. These gaps motivate the development of a dominant-mode-oriented and SCR-adaptive PI tuning method.

To address these gaps, this study embeds the physical relationship among grid strength, dominant-mode movement, and controller-parameter sensitivity into the PI parameter optimization process. To this end, a small-signal transient recovery characteristic matrix is established for the LVRT recovery stage of a grid-connected PMSG system, dominant-mode and parameter root-locus analyses are performed under varying SCR conditions, and an SCR-adaptive sensitivity-guided PSO method is proposed for coordinated PI tuning. In the proposed method, SCR-dependent damping constraints are used to enforce a minimum damping requirement under weak-grid conditions, while normalized dominant-eigenvalue sensitivity is introduced to guide the optimization priority of different PI parameters. Comparative and robustness simulations are then conducted to verify the effectiveness and adaptability of the proposed method under weak-grid, parameter-uncertainty, and fault-condition variations.

2. Small-Signal Modeling and Dominant-Mode Analysis of LVRT Recovery

The topology of the grid-side converter and grid-connected system of the PMSG is illustrated in Figure 1. The main circuit primarily consists of a DC bus, a full-bridge

converter, a filter inductor L_f , and a weak AC grid with an equivalent line inductance L_g (filter resistance and grid resistance losses are neglected in this paper). Here, V_{dc} represents the DC bus voltage, while V_g and θ_g denote the amplitude and phase angle of the grid voltage, respectively. The control system adopts a cascaded architecture, which is composed of an outer DC voltage loop, an inner current loop, the PLL, and a space pulse width modulation (SPWM) module. Additionally, $V_{pcc,d}$ and $V_{pcc,q}$, and i_d and i_q are defined as the components of the PCC voltage and the converter output current in the synchronous rotating dq reference frame, respectively, and θ_{pll} represents the tracking phase angle output by the PLL.

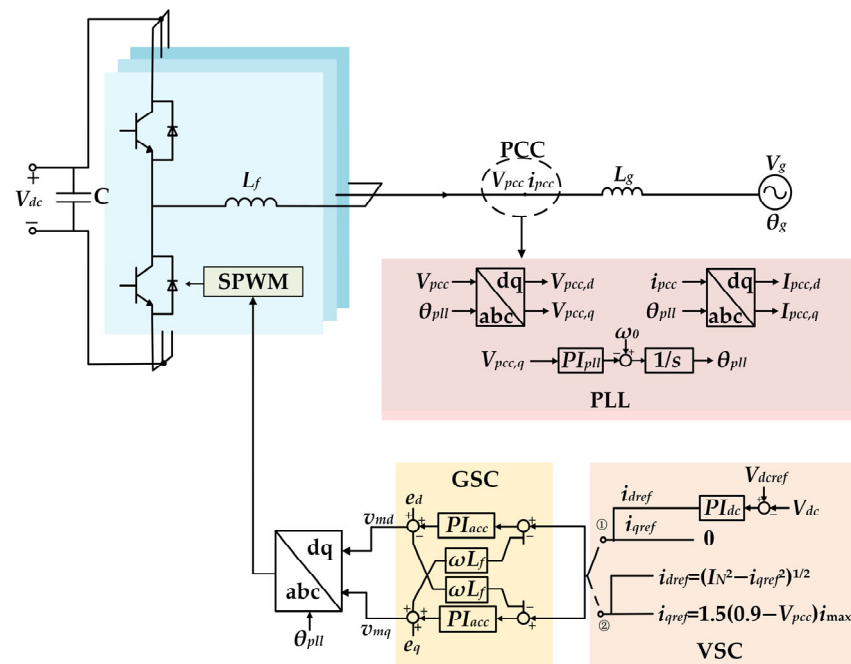


Figure 1. Topology of the PMSG system. Mode ① denotes the unity power tracking mode, and Mode ② denotes the reactive power support mode.

This paper focuses on the LVRT fault clearance stage, during which the converter switches back from the reactive power support mode (Mode ②) to the unity power tracking mode (Mode ①). After the fault is cleared, the system state begins to asymptotically converge to a new steady-state operating point. According to local linearization theory, the low-frequency oscillations and transient attenuation characteristics of the machine–grid interaction during this stage can be characterized by the local linearized dynamics around this operating point. Small-signal stability analysis has been widely used to characterize the interactions among converter control loops and grid-side impedance in renewable-energy grid-connected systems [19]. Based on this premise, the subsequent text will first establish the small-signal state-space model A of the system, i.e., the wind turbine transient recovery characteristic matrix A, and then conduct a multi-parameter eigenvalue sensitivity analysis.

2.1. Wind Turbine Transient Recovery Characteristic Matrix A

To analyze the transient recovery characteristics of the wind turbine during the LVRT recovery stage, eight small-signal state variables are selected and divided into three sub-systems according to their corresponding control loops, namely the current inner loop, the DC-link voltage outer loop, and the PLL. It should be noted that only the partitioned structure and physical interpretation of the transient recovery characteristic matrix A are presented in the main text. To avoid an excessively lengthy derivation in the main body,

the detailed algebraic derivation, variable elimination, and coefficient extraction processes of each block matrix are provided in Appendix A.

The state sub-vector of the current inner loop is defined as:

$$\Delta x_c = [\Delta i_d, \Delta i_q, \Delta \phi_d, \Delta \phi_q]^T \quad (1)$$

The state sub-vector of the DC-link voltage outer loop is defined as:

$$\Delta x_v = [\Delta V_{dc}, \Delta \phi_{vdc}]^T \quad (2)$$

The state sub-vector of the PLL is defined as:

$$\Delta x_{pll} = [\Delta \zeta_{pll}, \Delta \theta_{pll}]^T \quad (3)$$

where Δx_c denotes the state sub-vector of the current inner loop. Δi_d and Δi_q are the dq-axis current perturbations, and $\Delta \phi_d$ and $\Delta \phi_q$ are the integral state perturbations of the dq-axis current PI controllers, respectively. Δx_v denotes the state sub-vector of the DC-link voltage outer loop, where ΔV_{dc} is the DC-link voltage perturbation, and $\Delta \phi_{vdc}$ is the integral state perturbation of the DC-link voltage PI controller. Δx_{pll} denotes the state sub-vector of the PLL, where $\Delta \zeta_{pll}$ is the internal integral state perturbation of the PLL, and $\Delta \theta_{pll}$ is the output phase-angle perturbation of the PLL. Therefore, the overall small-signal state vector of the system can be written as:

$$\Delta x = [\Delta x_c^T, \Delta x_v^T, \Delta x_{pll}^T]^T \quad (4)$$

Based on the above state-variable partition, small-signal linearization is performed on the current inner loop, the DC-link voltage outer loop, and the PLL subsystem around the steady-state operating point after fault clearance. The following partitioned state equations can be obtained:

$$\begin{cases} \Delta \dot{x}_c = A_{cc}\Delta x_c + A_{cv}\Delta x_v \\ \Delta \dot{x}_v = A_{vc}\Delta x_c + A_{vv}\Delta x_v \\ \Delta \dot{x}_{pll} = A_{pc}\Delta x_c + A_{pp}\Delta x_{pll} \end{cases} \quad (5)$$

where A_{cc} characterizes the physical filtering and current tracking dynamics of the current inner loop, and A_{cv} represents the coupling effect of the DC-link voltage outer loop on the active current command. A_{vv} characterizes the closed-loop dynamics of the DC-link voltage outer loop, and A_{vc} describes the feedback effect of grid-side current variations on the DC-link energy balance. A_{pp} represents the damping and tracking dynamics of the PLL, while A_{pc} characterizes the machine–grid coupling effect caused by the influence of current perturbations on the PLL through PCC voltage distortion under weak grid conditions. The detailed algebraic derivation and coefficient extraction process of each block matrix are provided in Appendix A.

Therefore, the transient recovery characteristic matrix A of the wind turbine during the LVRT recovery stage can be written as:

$$A = \begin{bmatrix} A_{cc} & A_{cv} & 0 \\ A_{vc} & A_{vv} & 0 \\ A_{pc} & 0 & A_{pp} \end{bmatrix} \quad (6)$$

The partitioned structure of matrix A indicates that under strong grid conditions, the grid equivalent inductance L_g is relatively small, and the coupling terms in A_{pc} tend to be negligible. Therefore, the control loops are approximately decoupled. In contrast, under

weak grid conditions, a larger L_g makes current perturbations more likely to cause PCC voltage distortion, thereby strengthening the dynamic coupling between the current inner loop and the PLL. This coupling effect reduces the transient damping of the system, drives the dominant eigenvalues toward the imaginary axis, and induces voltage overshoot and secondary oscillations after fault clearance. Similar PLL-related modal coupling has also been reported in grid-following PMSG wind power systems under weak-grid conditions [20].

To preliminarily verify the influence of SCR on the LVRT recovery dynamics, three typical values of the grid equivalent inductance L_g are selected, corresponding to SCR = 5, SCR = 2.5, and SCR = 1.5. Under fixed empirical PI parameters, a three-phase short-circuit fault is applied at the PCC at 2 s, causing the PCC voltage to drop to 0.2 p.u., and the fault is cleared at 2.625 s. The PCC voltage recovery waveforms under different SCR conditions are shown in Figure 2. It can be observed that as SCR decreases, the voltage overshoot and oscillation amplitude after fault clearance increase significantly. This indicates that the reduction in grid strength intensifies the coupling between the PLL and the current inner loop and weakens the transient stability of the system.

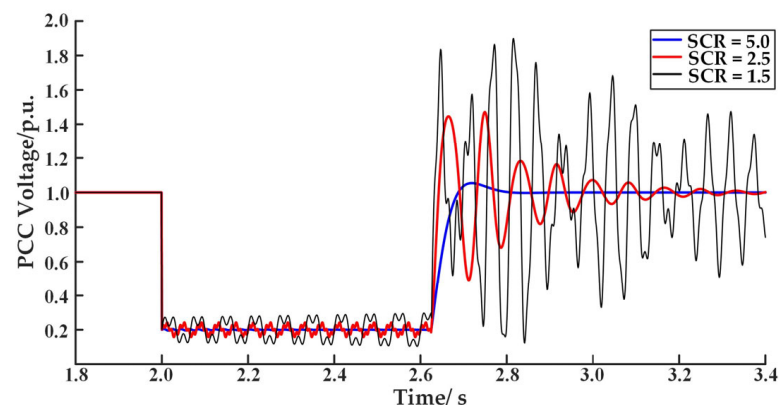


Figure 2. Transient voltage recovery waveforms at the PCC under different SCRs during a three-phase short-circuit fault.

2.2. Dominant Eigenvalue Extraction and Root Locus Analysis During the LVRT Recovery Phase

Eigenvalue-based small-signal stability criteria have been widely used to evaluate the stability margin of PMSG-based wind power systems [21]. Based on the transient recovery characteristic matrix A established in Section 2.1, the dominant mode is extracted using the time-scale separation concept of linear systems, and the mapping relationship between the eigenvalues in the complex plane and the time-domain transient recovery indices is established. Matrix A contains eight eigenvalues, corresponding to dynamic modes at different time scales in the wind turbine grid-connected system. During the LVRT recovery stage, the state response can be expressed as the linear superposition of all modal responses:

$$\Delta \mathbf{x}(t) = \sum_{i=1}^8 c_i \mathbf{V}_i e^{\lambda_i t} \quad (7)$$

where λ_i is the i -th eigenvalue, $\mathbf{V}_i$ is the corresponding right eigenvector, and c_i is the modal excitation coefficient determined by the initial perturbation.

According to time-scale separation theory, the transient components corresponding to eigenvalues far from the imaginary axis decay rapidly, whereas the eigenvalues close to the imaginary axis decay more slowly and dominate the transient trajectory of the system as it converges to the steady state. Therefore, the pair of complex conjugate roots closest to the imaginary axis, which consistently exhibits the slowest decay characteristic and dominates

the PCC-voltage recovery response within the investigated SCR range, is selected as the dominant eigenvalue, denoted as:

$$\lambda_{\text{dom}} = \sigma \pm j\omega_d \quad (8)$$

where σ and ω_d are the real and imaginary parts of the dominant eigenvalue, respectively. Under the influence of the dominant mode, the transient recovery process can be approximated as a typical second-order underdamped response. The damping ratio, settling time, and overshoot can be expressed as:

$$\begin{cases} \zeta = \frac{|\sigma|}{\sqrt{\sigma^2 + \omega_d^2}} \\ T_s = \frac{4}{|\sigma|} \\ M_p = e^{-\frac{\pi\zeta}{\sqrt{1-\zeta^2}}} \times 100\% \end{cases} \quad (9)$$

The above relationships indicate that a more negative σ , or equivalently a larger $|\sigma|$, means that the dominant eigenvalue is located deeper in the left half-plane, resulting in a shorter transient recovery time. A larger damping ratio ζ corresponds to a smaller overshoot and better transient stability.

Corresponding to the voltage recovery waveforms under different SCR conditions in Figure 2, the same system parameters and empirical PI parameters are adopted to calculate the dominant eigenvalue distribution of the transient recovery characteristic matrix A , as shown in Figure 3. It can be observed that as SCR decreases, the dominant eigenvalues gradually move closer to the imaginary axis, indicating reduced transient damping and more obvious low-frequency oscillations and overshoot during the recovery process. This eigenvalue movement trend is highly consistent with the time-domain recovery waveforms in Figure 2.

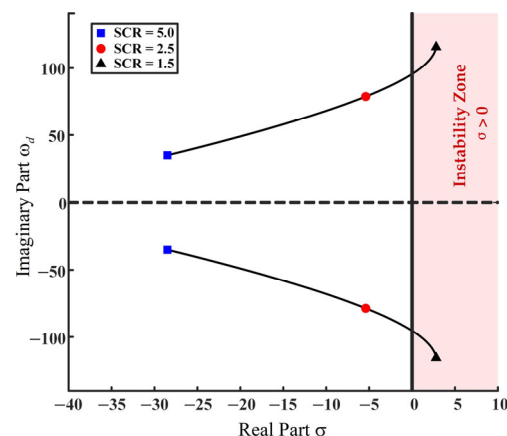


Figure 3. Locations of dominant eigenvalues λ_{dom} under different SCRs.

It should be noted that the dominant-mode selection in this study is based on the modal decay rate and its consistency with the time-domain LVRT recovery behavior. Within the investigated SCR range, the selected complex-conjugate eigenvalue pair remains the closest oscillatory mode to the imaginary axis and therefore exhibits the slowest attenuation among the system modes. Moreover, its movement trend under different SCR conditions is consistent with the PCC-voltage recovery waveforms, indicating that this mode captures the main low-frequency recovery dynamics after fault clearance. Although a complete participation-factor or modal-residual analysis could provide additional information on state contributions and modal observability, the present study focuses on using the domi-

nant eigenvalue as a physically interpretable indicator for SCR-adaptive PI tuning. The consistency between the dominant-mode prediction and nonlinear time-domain simulation is further verified in Section 4.2.

Therefore, the core objective of parameter optimization can be summarized as follows: under the premise of satisfying physical and stability constraints, the dominant eigenvalues should be moved leftward within the physically feasible and damping-constrained region, while their damping ratio should be increased. Since the locations of the dominant eigenvalues are jointly affected by the PI parameters of the PLL, the current inner loop, and the DC-link voltage outer loop, it is necessary to further analyze how different PI parameters drive the movement of the dominant eigenvalues, thereby providing a quantitative basis for the subsequent parameter optimization algorithm.

Although the above analysis confirms the relationship between dominant eigenvalue movement and LVRT recovery performance, the specific mechanism by which the six PI parameters affect the trajectory of λ_{dom} remains to be further clarified. Therefore, the parameter root locus evolution analysis is introduced in the next subsection as a quantitative tool to determine how different PI parameters influence the movement of λ_{dom} .

2.3. Parameter Root Locus Evolution Analysis Considering Grid Strength

To quantitatively characterize the influence of converter control parameters on system transient stability under different grid strengths, the nonlinear evolution trajectories of the dominant eigenvalues are further analyzed when the six PI parameters vary under $\text{SCR} = 2.5$ and $\text{SCR} = 1.5$. The root locus trajectories corresponding to decreased PI parameters are shown in Figure 4, while those corresponding to increased PI parameters are shown in Figure 5. In these figures, point X denotes the initial dominant pole under fixed empirical engineering parameters, and each trajectory represents the movement direction and magnitude of the dominant eigenvalue in the complex plane when a single PI parameter varies. It should be clarified that the shaded region in Figures 3–5 denotes the right-half-plane instability zone, i.e., the region with $\sigma > 0$. The left half-plane with $\sigma < 0$ corresponds to the stable region, and a leftward movement of the dominant eigenvalue indicates an increase in the transient attenuation rate and stability margin. Different from unified transient control methods for hybrid AC/DC microgrids [22], which usually focus on coordinated power regulation among multiple converters or subgrids, the root-locus analysis in this study is used to identify the loop-specific influence of PLL, current-loop, and DC-link voltage-loop parameters on the dominant LVRT recovery mode under varying SCR conditions.

The evolution trajectories of the dominant eigenvalues indicate that the PI parameters of different control loops affect transient performance and stability boundaries through different mechanisms, and such effects are closely related to grid strength.

For the PLL control loop, increasing $K_{p,pll}$ and $K_{i,pll}$ drives the dominant eigenvalues rightward, resulting in an obvious low-damping or even unstable tendency. Under $\text{SCR} = 2.5$, this rightward movement is relatively slow. In contrast, under $\text{SCR} = 1.5$, the weaker grid intensifies the coupling between the PLL and the current inner loop, causing a more significant rightward shift of the dominant eigenvalues and even bringing them close to the unstable region. Conversely, appropriately decreasing the PLL parameters can pull the dominant eigenvalues back into the left half-plane and improve system damping.

For the DC-link voltage outer loop, increasing $K_{p,dc}$ and $K_{i,dc}$ generally helps enhance the post-fault energy recovery capability and moves the dominant eigenvalues leftward, thereby improving the transient attenuation speed. However, under the weak grid condition of $\text{SCR} = 1.5$, the stabilizing traction capability of the DC-link voltage outer loop is compressed due to the limited grid support capability, and its leftward regulation effect is

weaker than that under SCR = 2.5. Conversely, decreasing the DC-link voltage-loop parameters weakens the DC-side energy regulation capability, moves the dominant eigenvalues rightward, and reduces system damping.

For the current inner loop, when $K_{p,i}$ and $K_{i,i}$ are independently increased or decreased, the movement amplitude of the dominant eigenvalues in the complex plane is relatively small, mainly appearing as local fine adjustment. This indicates that in the low-frequency dominant mode of the LVRT recovery stage studied in this paper, the traction effect of the current-loop parameters on the dominant eigenvalues is weaker than that of the PLL and DC-link voltage-loop parameters.

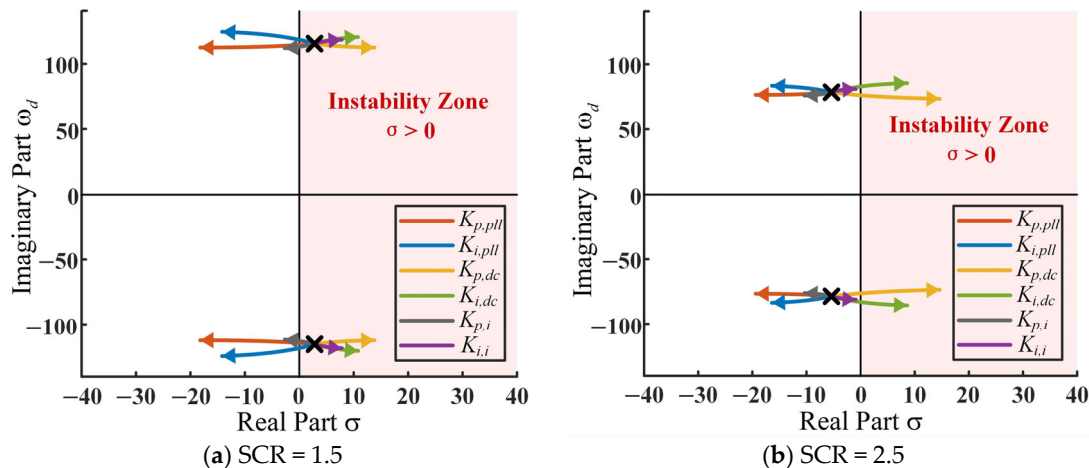


Figure 4. Parameter Root Locus Evolution Analysis with decreasing PI parameters: (a) under SCR = 1.5; (b) under SCR = 2.5. The arrows indicate the movement directions of the dominant eigenvalues, the symbol $\times$ marks the initial dominant pole, and the shaded region denotes the instability zone with $\sigma > 0$.

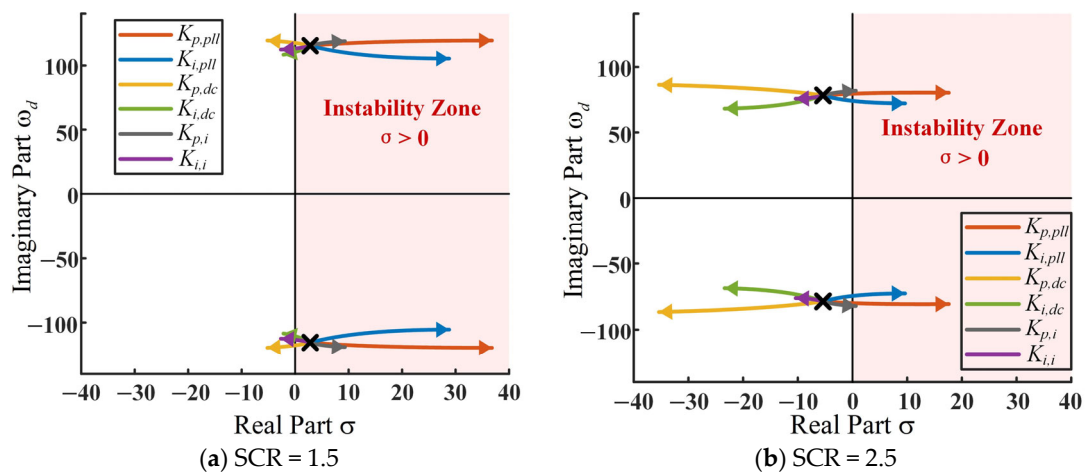


Figure 5. Parameter Root Locus Evolution Analysis with increasing PI parameters: (a) under SCR = 1.5; (b) under SCR = 2.5. The arrows indicate the movement directions of the dominant eigenvalues, the symbol $\times$ marks the initial dominant pole, and the shaded region denotes the instability zone with $\sigma > 0$.

To more intuitively summarize the influence of PI parameters from different control loops on the locations of the dominant eigenvalues, Table 1 presents the effects of PI parameter variations on the movement direction of the dominant eigenvalues under different SCR conditions.

Table 1. Impact of PI parameters of different control loops on dominant eigenvalue locations under varying SCR conditions (empirical engineering parameters).

PI	Parameter Trend	SCR = 2.5	SCR = 1.5
$K_{p,pll}, K_{i,pll}$	Increase	Slowly shift rightward	Rapidly shift rightward and approach the unstable region
	Decrease	Move leftward and improve damping	Move leftward and significantly improve damping
$K_{p,dc}, K_{i,dc}$	Increase	Shift leftward with strong regulation capability	Shift leftward, but the regulation capability is weakened
	Decrease	Slowly shift rightward	Rapidly shift rightward and reduce damping
$K_{p,i}, K_{i,i}$	Increase	Slight local movement; weak influence	Slight local movement; weak influence
	Decrease		

Figures 4 and 5, together with Table 1, show that a weak-grid environment not only reduces the transient stability margin of the system but also changes the regulation capability of different PI parameters on the dominant eigenvalues. The PLL parameters exert a strong destabilizing traction under weak-grid conditions because the PLL directly participates in the grid-synchronization dynamics and is strongly affected by PCC-voltage distortion caused by grid impedance. The DC-link voltage-loop parameters provide a certain stabilizing traction capability by regulating the post-fault energy imbalance and supporting the recovery of the DC-link and PCC voltages. In contrast, the current-loop parameters mainly provide fast local current tracking and bandwidth-limited inner-loop regulation. Therefore, for the low-frequency dominant recovery mode considered in this study, their influence on the dominant eigenvalue trajectory is relatively weak compared with that of the PLL and DC-link voltage-loop parameters. This finding does not mean that the current loop is unimportant for converter control; rather, it indicates that current-loop parameters can be de-emphasized only in the dominant-mode-oriented search priority under weak-grid LVRT recovery conditions. In the proposed SG-PSO framework, all six PI parameters remain included in the optimization variables, while their update priority is dynamically determined by the normalized dominant-eigenvalue sensitivity. Different from unified transient control methods for hybrid AC/DC microgrids [22], which usually focus on coordinated power regulation among multiple converters or subgrids, the loop-specific analysis in this study is used to identify the relative influence of PLL, current-loop, and DC-link voltage-loop parameters on the dominant recovery mode of a single grid-connected PMSG system under varying SCR conditions. Such a complex distribution of parameter sensitivity makes it difficult for traditional empirical tuning methods to achieve a balance between stability and rapidity. Therefore, an improved particle swarm optimization algorithm incorporating SCR-adaptive constraints and sensitivity-guided dimension reduction is proposed in the next section to realize the globally coordinated optimization of the six-dimensional PI parameters.

3. SCR-Adaptive Sensitivity-Guided PI Tuning Method

As analyzed in Section 2, during the LVRT recovery stage, variations in SCR significantly change the traction effects of the PLL, the inner current loop, and the DC-link voltage outer loop on the dominant eigenvalues. As SCR decreases, the coupling between the PLL and the inner current loop is strengthened, causing the dominant eigenvalues to approach the imaginary axis and reducing the damping margin of the system. This further aggravates PCC voltage overshoot and secondary oscillations. Therefore, PI tuning should not rely solely on empirical trial-and-error or blind global search using conventional intelli-

gent algorithms, but should be combined with the dominant-mode analysis established in Section 2.

On this basis, this paper proposes a sensitivity-guided dimension-reduced PSO algorithm with SCR-adaptive constraints, denoted as SG-PSO. Based on the transient recovery characteristic matrix A , the six PI parameters of the PLL, the inner current loop, and the DC-link voltage outer loop are selected as the optimization variables. The real part of the dominant eigenvalue and the damping margin are used as the core evaluation criteria. Compared with conventional PSO, SG-PSO does not perform undifferentiated search in the full six-dimensional parameter space. Instead, it dynamically selects key parameters for focused optimization according to the normalized sensitivity of the dominant eigenvalue with respect to each PI parameter, thereby reducing the effective optimization dimension and enhancing the physical interpretability of the optimization results.

3.1. Optimization Variables, Objective Function, and SCR-Adaptive Constraints

The six PI parameters of the PLL, the inner current loop, and the DC-link voltage outer loop are selected as the optimization variables: $\Theta = [K_{p,pll}, K_{i,pll}, K_{p,i}, K_{i,i}, K_{p,dc}, K_{i,dc}]^T$. For a given SCR condition, matrix A can be expressed as a function of Θ and SCR. The relationship among the dominant eigenvalue, damping ratio, recovery time, and overshoot has already been established in Section 2. According to this relationship, a more leftward real part of the dominant eigenvalue indicates a faster transient attenuation rate, while a larger damping ratio corresponds to smaller PCC voltage overshoot and weaker secondary oscillations. Therefore, the optimization objective of this paper is to move the real part of the dominant eigenvalue leftward as much as possible while satisfying damping and physical constraints. The objective function is defined as:

$$\min_{\Theta} f(\Theta, SCR) = \sigma(\Theta, SCR) \quad (10)$$

where $\sigma(\Theta, SCR)$ denotes the real part of the dominant eigenvalue under the current PI parameters and SCR condition. Since the real part of the dominant eigenvalue of a stable system is negative, minimizing this objective function is equivalent to driving the dominant eigenvalue toward the left half-plane, thereby shortening the LVRT recovery time. However, using only the leftward movement of the real part as the optimization objective is insufficient. If the algorithm excessively pursues recovery speed, the damping margin may become inadequate, and new oscillations may even be induced under weak-grid conditions. Therefore, the proposed objective function and damping constraint are designed to play complementary roles. The eigenvalue real-part minimization term improves the transient attenuation speed by driving the dominant eigenvalue leftward, whereas the SCR-adaptive damping constraint prevents the optimized solution from becoming insufficiently damped, especially when the grid strength is low. In this sense, the optimization problem balances rapid voltage recovery and oscillation suppression in the eigenvalue domain. This idea is also consistent with unified transient control concepts for hybrid microgrids [22], where static operating requirements and transient recovery requirements need to be coordinated under varying grid conditions. Different from such system-level power-regulation methods, the proposed formulation translates the grid-strength-dependent transient requirement into an SCR-adaptive lower bound of the dominant-mode damping ratio for PI parameter tuning. Therefore, an SCR-adaptive damping constraint is introduced:

$$\begin{aligned} \zeta(\Theta, SCR) &\geq \zeta_{min}(SCR) \\ \zeta_{min}(SCR) &= \zeta_0 + k_{\zeta} \max(0, SCR_{th} - SCR) \end{aligned} \quad (11)$$

where $\zeta(\Theta, \text{SCR})$ is the dominant-mode damping ratio calculated according to the definition in Section 2, ζ_0 is the basic damping threshold, k_ζ is the damping compensation coefficient, and SCR_{th} is the critical threshold of grid strength. When SCR is lower than SCR_{th} , the damping lower bound increases as SCR decreases, forcing the algorithm to prioritize overshoot and secondary oscillation suppression under weak-grid conditions. When SCR is higher than or equal to SCR_{th} , the damping constraint remains at the basic threshold, allowing the algorithm to adopt less conservative PI parameter settings and improve the recovery speed while maintaining the required damping margin.

Meanwhile, considering engineering factors such as digital control delay, PWM delay, sampling frequency, converter current limitation, and high- and low-frequency mode separation, the dominant eigenvalue cannot be pushed indefinitely into the left half-plane. Therefore, the following safety constraint is imposed on its real part:

$$\sigma_{\text{ref}} \leq \sigma(\Theta, \text{SCR}) \leq -\varepsilon \quad (12)$$

where σ_{ref} denotes the safety lower bound of the real part, which limits the maximum achievable recovery speed of the system, and ε is a small positive value used to ensure that the dominant eigenvalue remains in the left half-plane with a basic stability margin. In addition, the six PI parameters should satisfy the boundary constraint:

$$\Theta_{\min}(\text{SCR}) \leq \Theta \leq \Theta_{\max}(\text{SCR}) \quad (13)$$

where $\Theta_{\min}(\text{SCR})$ and $\Theta_{\max}(\text{SCR})$ are the lower and upper bounds of the PI parameters under the current SCR condition, respectively. This constraint is consistent with the parameter root locus analysis in Section 2. Under weak-grid conditions, the upper bounds of the PLL parameters should be properly restricted to weaken the low-damping coupling caused by the PLL, which is consistent with the tuning requirement of grid-following converters under extremely weak-grid connections [9]. Meanwhile, the DC-link voltage loop should retain sufficient energy recovery capability, and the inner current-loop parameters should remain within the feasible control bandwidth.

3.2. Construction of the Comprehensive Fitness Function

To handle the optimization objective and constraints simultaneously in SG-PSO, an exterior penalty function is adopted to construct the comprehensive fitness function:

$$J(\Theta, \text{SCR}) = f(\Theta, \text{SCR}) + M_1 [\max(0, \zeta_{\min}(\text{SCR}) - \zeta)]^2 + M_2 [\max(0, \sigma_{\text{ref}} - \sigma)]^2 + M_3 [\max(0, \sigma + \varepsilon)]^2 + M_4 \sum_{j=1}^6 P_j \quad (14)$$

where:

$$P_j = [\max(0, \Theta_{\min,j} - \Theta_j)]^2 + [\max(0, \Theta_j - \Theta_{\max,j})]^2 \quad (15)$$

Here, M_1 , M_2 , M_3 , and M_4 are large positive penalty coefficients. When a particle simultaneously satisfies the damping constraint, the real-part safety constraint, and the parameter boundary constraint, all penalty terms become zero, and the fitness function degenerates into the objective function $f(\Theta, \text{SCR})$. When any constraint is violated, the corresponding penalty term is activated, forcing the particle to return to the safe feasible region in subsequent iterations.

This fitness function is consistent with the algorithm comparison in Section 4. PSO, OBO-PI, and SG-PSO all perform six-dimensional PI parameter optimization under the same objective function and physical constraints. Therefore, the subsequent simulation re-

sults can reflect the differences among the search mechanisms of the algorithms themselves, rather than differences caused by inconsistent objectives or constraints.

3.3. Normalized Real-Part Sensitivity Model

When conventional PSO performs global search in the six-dimensional PI parameter space, all parameters are updated simultaneously in each iteration, which may lead to ineffective search. The parameter root locus analysis in Section 2 shows that different PI parameters have significantly different influence strengths on the dominant eigenvalues, and this difference varies with SCR. Therefore, it is necessary to identify the parameters that have the most significant influence on the real part of the dominant eigenvalue under the current operating condition and use them as the priority search targets. Eigenvalue sensitivity has been widely used to identify the key parameters responsible for poorly damped modes and to provide directional information for control-parameter tuning [23]. For the j -th PI parameter, the sensitivity of the dominant eigenvalue with respect to this parameter can be expressed as:

$$\frac{\partial \lambda_{dom}}{\partial \Theta_j} = \frac{W_{dom}^H \frac{\partial A}{\partial \Theta_j} V_{dom}}{W_{dom}^H V_{dom}} \quad (16)$$

where V_{dom} and W_{dom} are the right and left eigenvectors corresponding to the dominant eigenvalue, respectively, and the superscript H denotes the conjugate transpose. This sensitivity reflects the influence of PI parameter variations on the location of the dominant eigenvalue through the dynamic coupling channels in matrix A .

Since the optimization objective of this paper mainly focuses on moving the real part of the dominant eigenvalue leftward, the real part of the sensitivity is emphasized. Considering that the PI parameters of different control loops have different magnitudes and value ranges, directly comparing the absolute sensitivities may lead to scale bias. Therefore, the normalized real-part sensitivity is defined as:

$$S_{\sigma,j} = \frac{\Delta \Theta_j}{|\sigma| + \delta} \operatorname{Re} \left(\frac{\partial \lambda_{dom}}{\partial \Theta_j} \right) \quad (17)$$

where $\Delta \Theta_j = \Theta_{\max,j} - \Theta_{\min,j}$ is the search interval width of the j -th parameter, and δ is a positive value used to avoid an excessively small denominator. $|S_{\sigma,j}|$ is used to measure the influence strength of the j -th PI parameter on the transient attenuation rate, while the sign of $S_{\sigma,j}$ is used to determine the parameter adjustment direction. When $S_{\sigma,j} > 0$, increasing this parameter moves the real part of the dominant eigenvalue rightward, which is unfavorable to system stability. When $S_{\sigma,j} < 0$, increasing this parameter helps move the dominant eigenvalue leftward, which is beneficial for improving the recovery speed.

3.4. Sensitivity-Guided Dimension-Reduced PSO Update Mechanism

Based on the normalized real-part sensitivity, SG-PSO dynamically determines the active parameter set in each iteration. Let the six-dimensional normalized real-part sensitivity of the current global best particle at the k -th iteration be:

$$[S_{\sigma,1}^k, S_{\sigma,2}^k, \dots, S_{\sigma,6}^k] \quad (18)$$

The sensitivities are sorted in descending order according to $|S_{\sigma,j}^k|$, and the top m parameters are selected to form the active parameter set:

$$\left\{ j \mid |S_{\sigma,j}^k| \text{ belongs to the top } m \text{ values} \right\} \quad (19)$$

In this paper, $m = 2$. This value was selected as a compromise between optimization focus and search diversity. When $m = 1$, only the most sensitive PI parameter is updated in each iteration, which provides the strongest dimension reduction but may make the search overly dependent on a single dominant direction and weaken the coordination among the PLL, current-loop, and DC-link voltage-loop parameters. When $m = 3$ or $m = 4$, more parameters are updated simultaneously, which improves search diversity but gradually weakens the dimension-reduction effect and makes the search process closer to conventional full-dimensional PSO. Therefore, $m = 2$ is adopted to preserve the sensitivity-guided search direction while still maintaining sufficient coordination among multiple control loops. Since the proposed SG-PSO framework updates the active parameter set at every iteration according to the normalized eigenvalue sensitivities, selecting the two most sensitive parameters allows the algorithm to emphasize the dominant control directions while still maintaining coordinated optimization among all six PI parameters through the dynamic update mechanism. That is, in each iteration, the particle swarm focuses only on the two most sensitive PI parameters, while the remaining parameters are temporarily kept unchanged. It should be noted that Ω_{active}^k is not a fixed set but is dynamically updated with the iteration process and SCR condition. Therefore, this mechanism does not permanently exclude any PI parameter but adaptively adjusts the optimization focus at different search stages. For the parameters in the active set, SG-PSO introduces a sensitivity-sign guidance term into the conventional PSO velocity update equation:

$$\begin{aligned} v_{i,j}^{k+1} &= \omega v_{i,j}^k + c_1 r_1 (p_{i,j}^k - \Theta_{i,j}^k) + c_2 r_2 (g_j^k - \Theta_{i,j}^k) - c_3 r_3 \text{sgn}(S_{\sigma,j}^k) \Delta \Theta_{i,j}, \quad j \in \Omega_{active}^k \\ \Theta_{i,j}^{k+1} &= \text{Proj}[\Theta_{min,j}, \Theta_{max,j}] (\Theta_{i,j}^k + v_{i,j}^{k+1}) \end{aligned} \quad (20)$$

where $v_{i,j}^k$ and $\Theta_{i,j}^k$ are the velocity and position of the i -th particle in the j -th dimension, respectively; $p_{i,j}^k$ is the personal best position; g_j^k is the global best position; ω is the inertia weight; c_1 and c_2 are the learning factors; c_3 is the sensitivity-guidance coefficient; r_1 , r_2 , and r_3 are random numbers within $[0, 1]$; and $\text{Proj}(\cdot)$ is the boundary projection operator.

The function of this guidance term is to update the particles along the direction that is beneficial for the leftward movement of the dominant eigenvalue. When $S_{\sigma,j}^k > 0$, increasing this parameter moves the real part of the dominant eigenvalue rightward; therefore, the guidance term drives this parameter to decrease. When $S_{\sigma,j}^k < 0$, increasing this parameter helps move the dominant eigenvalue leftward; therefore, the guidance term drives this parameter to increase. In this way, SG-PSO reduces reverse search and ineffective iterations, making the optimization process consistent with the dominant-mode evolution revealed in Section 2. For inactive parameters, a temporary freezing strategy is adopted:

$$\Theta_{i,j}^{k+1} = \Theta_{i,j}^k, \quad j \notin \Omega_{active}^k \quad (21)$$

Since the active set is recalculated in subsequent iterations, temporary freezing does not mean that inactive parameters are excluded from optimization. Instead, it avoids ineffective search in low-sensitivity dimensions at the current stage. This mechanism reduces the search dimension while retaining the global coordinated optimization capability among the six PI parameters.

3.5. Procedure of the Proposed SG-PSO Algorithm

Based on the above optimization objective, SCR-adaptive constraints, and normalized real-part sensitivity model, the procedure of the proposed SG-PSO algorithm is illustrated in Figure 6.

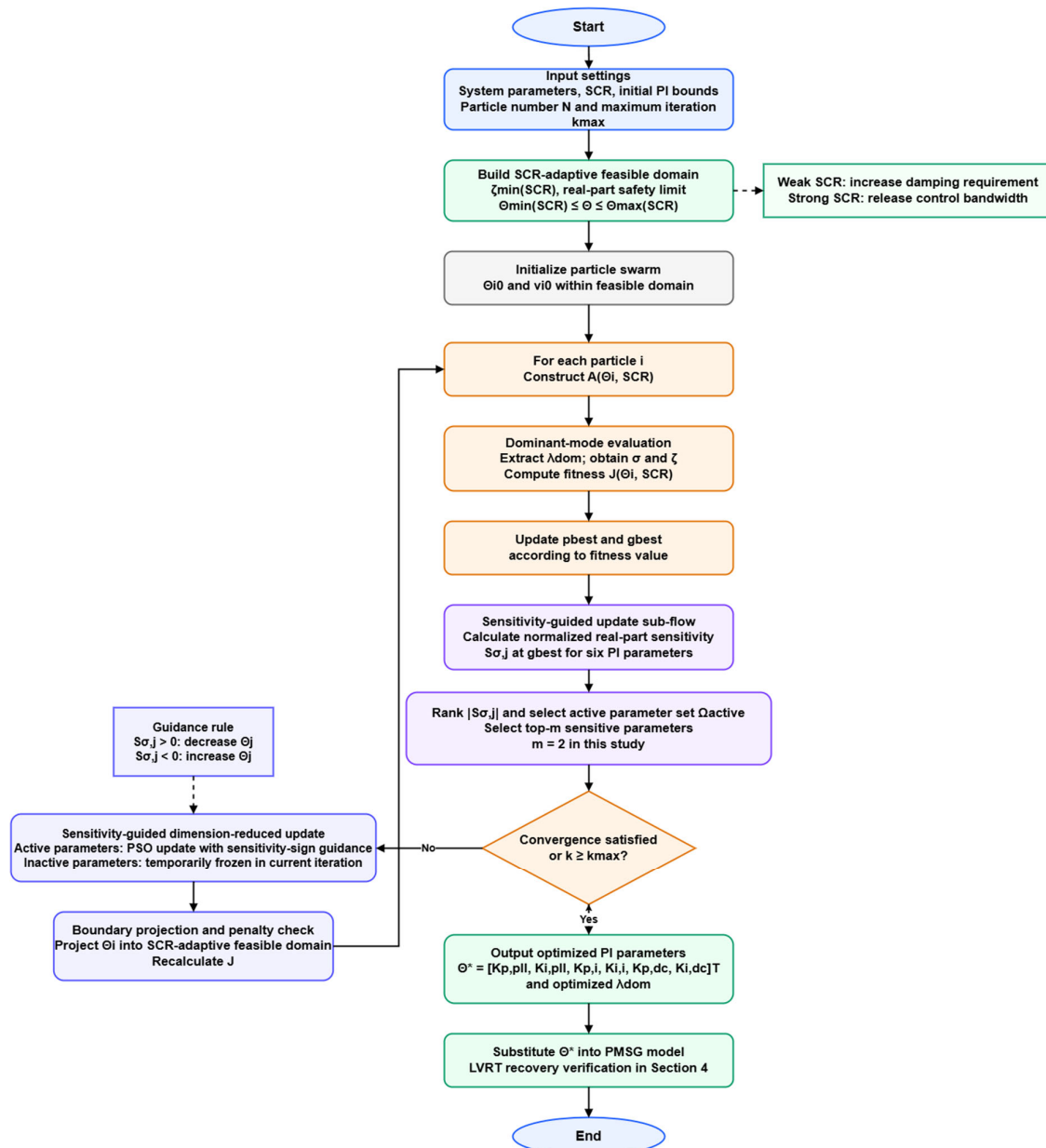


Figure 6. Flowchart of the proposed SG-PSO algorithm with SCR-adaptive constraints and sensitivity-guided dimension reduction. The superscript * in Θ^* denotes the optimized PI parameter vector.

The “No” branch of the termination condition returns to the dominant-eigenvalue evaluation and fitness calculation stage, indicating that the particle swarm continues the iterative optimization until convergence is satisfied or the maximum iteration number is reached.

As shown in Figure 6, SG-PSO combines SCR-adaptive constraints, dominant-eigenvalue sensitivity information, and the conventional PSO optimization mechanism. It should be noted that the proposed SG-PSO framework retains the conventional PSO search mechanism. The main contribution of this work lies in the incorporation of normalized real-part sensitivity guidance and SCR-adaptive damping constraints, which reduce the effective optimization dimension and improve the physical interpretability of the parameter-tuning process. Therefore, the observed improvement of the proposed method in the tested cases mainly originates from the physically informed optimization framework rather than modifications to the underlying stochastic search algorithm.

The SCR-adaptive feasible domain in Figure 6 is determined by two coupled grid-strength-dependent rules. First, when SCR decreases, the lower bound of the dominant-mode damping ratio is increased, forcing the particles to search within a more conservative feasible domain and prioritizing the suppression of PCC-voltage overshoot and secondary oscillations. Second, the parameter boundary constraints, especially those associated with the PLL bandwidth, are adjusted according to the grid strength so that overly aggressive PLL tuning can be avoided under weak-grid conditions. When SCR is relatively high, the damping constraint is relaxed to the basic threshold, allowing the optimization process to release part of the control bandwidth and improve the voltage recovery speed while maintaining the required stability margin.

This grid-strength-dependent adjustment is consistent with the idea of coordinating static operating requirements and transient recovery requirements in unified transient control frameworks for hybrid AC/DC microgrids [22]. However, the proposed SG-PSO applies this idea in the eigenvalue-domain PI tuning problem of a grid-connected PMSG system. Specifically, SCR variation is translated into an adaptive damping lower bound and feasible PI-parameter domain, while dominant-mode sensitivity is used to determine which control parameters should be prioritized during the optimization process. Therefore, Figure 6 represents not only an optimization procedure but also a physically informed tuning logic that links grid strength, damping margin, control bandwidth, and dominant-mode movement.

4. Simulation Results and Discussion

Advanced converter-control methods, such as FCS-MPC, have also been applied to enhance the LVRT performance of PMSG-based wind energy systems [24]. To verify the effectiveness of the proposed PI parameter optimization method with SCR-adaptive constraints and normalized real-part sensitivity guidance, a grid-connected simulation model of a direct-drive PMSG wind turbine was established in MATLAB/Simulink. The proposed SG-PSO method was implemented and validated in MATLAB/Simulink R2023b. A PMSG-based wind power generation system together with its associated control loops was modeled using Simulink and Simscape Electrical Specialized Power Systems. Simulations were performed using the FixedStepDiscrete solver with a fixed-step size of 1×10^{-5} s, while the power-system network was configured in discrete mode through the powergui block. The same simulation configuration was adopted for all case studies and robustness tests to ensure consistency and reproducibility of the obtained results. The main system parameters are listed in Table 2. To further demonstrate the superiority of the proposed SG-PSO method over both conventional and recently reported intelligent optimization algorithms, the conventional particle swarm optimization algorithm (denoted as PSO), a recently reported one-to-one-based optimizer tuned PI controller (denoted as OBO-PI [25]), and the proposed SG-PSO are compared. To ensure a fair comparison, the three algorithms are implemented under the same PMSG grid-connected model, PI parameter boundaries, optimization objective, and physical constraints for the six-dimensional PI parameter optimization.

It should be noted that PSO, OBO-PI, and the proposed SG-PSO are metaheuristic optimization methods and may exhibit stochastic variations due to random initialization and random search operators. The purpose of the comparison in this study is not to provide a comprehensive statistical benchmark of metaheuristic algorithms, but to verify whether the proposed sensitivity-guided and SCR-adaptive tuning framework can improve LVRT recovery performance under identical model settings, parameter boundaries, objective functions, and physical constraints. Therefore, the same simulation configuration and optimization constraints are adopted for all compared methods. A complete statistical

evaluation based on multiple independent runs, confidence intervals, and significance tests is beyond the scope of the present mechanism-oriented study. Therefore, the comparison in this paper should be interpreted as a mechanism-oriented validation of the proposed SCR-adaptive sensitivity-guided tuning framework under consistent simulation and optimization settings.

Table 2. Parameters of the PMSG Grid-Connected System.

Main Parameters	Parameter Values
Rated Power	1.5 MW
Grid Voltage	690 V
Grid Frequency	50 Hz
DC-link Voltage	1500 V
L-type Filter	90 μ H
DC Capacitance	15 mF

4.1. Comparative Verification Under Weak Grid Condition SCR = 1.5

To verify the optimization effect of the proposed SG-PSO algorithm on multi-dimensional PI parameters under weak grid conditions, the short-circuit ratio is set to SCR = 1.5 in this case. A three-phase short-circuit fault is applied at the PCC at 2 s, causing the PCC voltage to drop to 0.2 p.u., and the fault is cleared at 2.625 s. After fault clearance, the system enters the low-voltage ride-through recovery stage. The PI parameters optimized by PSO, OOBO-PI, and the proposed SG-PSO are substituted into the simulation model, and comparative analysis is conducted in terms of PCC voltage recovery, DC-link voltage fluctuation, active/reactive power responses, and transient recovery indices.

Table 3 lists the optimized PI parameters obtained by different algorithms under SCR = 1.5. It can be observed that, compared with PSO and OOBO-PI, SG-PSO reduces the PLL control gains and appropriately increases the DC-link voltage-loop gains. This parameter tendency is consistent with the dominant-mode analysis presented above: reducing the PLL bandwidth helps suppress the low-damping oscillations caused by the coupling between the PLL and the current loop under weak grid conditions, while strengthening the DC-link voltage loop improves the post-fault energy recovery capability.

Table 3. Optimized PI parameters under SCR = 1.5.

Algorithm	$K_{p,pll}$	$K_{i,pll}$	$K_{p,i}$	$K_{i,i}$	$K_{p,dc}$	$K_{i,dc}$
PSO	52.0	1450	0.62	95	0.42	35
OOBO-PI	38.5	980	0.64	98	0.55	48
SG-PSO	26.0	620	0.66	100	0.73	70

Figure 7 shows the transient PCC voltage recovery waveforms under different optimization algorithms. It can be observed that the parameters optimized by the conventional PSO still lead to an obvious voltage overshoot and a relatively long recovery time after fault clearance. This indicates that the optimized parameters obtained by PSO are less effective in suppressing the low-damping oscillation caused by machine–grid coupling under weak-grid conditions. Compared with PSO, OOBO-PI improves the PCC-voltage recovery performance to a certain extent. This result suggests that the optimized parameter set obtained by OOBO-PI provides a better compromise between recovery speed and transient damping under weak-grid conditions. However, since OOBO-PI does not explicitly incorporate SCR-adaptive damping constraints and dominant-mode sensitivity guidance, its optimized parameters still provide limited suppression of the PLL–current-loop coupling effect under weak-grid conditions. In contrast, the proposed SG-PSO achieves the smallest

voltage overshoot and the shortest recovery time, demonstrating that the proposed method can effectively improve transient stability during the LVRT recovery stage.

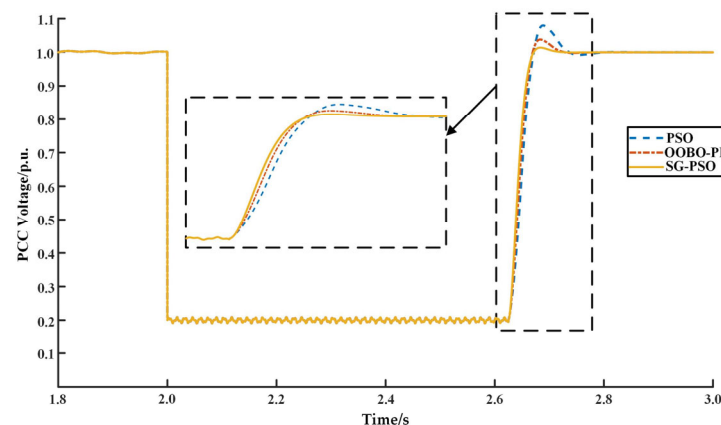


Figure 7. Comparison of transient voltage recovery waveforms at the PCC optimized by PSO, OBO-PI, and SG-PSO (SCR = 1.5).

The improvement observed in Figure 7 can be further attributed to the two main components of SG-PSO illustrated in Figure 6. First, the SCR-adaptive damping constraint forces the optimization process to maintain a sufficient damping margin under the weak-grid condition of SCR = 1.5, thereby suppressing the PCC-voltage overshoot and secondary oscillations after fault clearance. Second, the normalized dominant-eigenvalue sensitivity guidance identifies the PI parameters that have the strongest influence on the dominant recovery mode and prioritizes them during the dimension-reduced update process. As reflected by the optimized parameters in Table 3, SG-PSO reduces the PLL-gain to weaken the PLL-grid-impedance coupling and increases the DC-link voltage-loop gains to enhance post-fault energy recovery. Therefore, the waveform improvement observed in Figure 7 is not merely a result of stochastic optimization in the tested case, but is also associated with the SCR-adaptive damping constraint and sensitivity-guided parameter update mechanism embedded in the proposed SG-PSO framework.

Figure 8 further presents the DC-link voltage responses under different optimization algorithms. During grid voltage dips, the active power transfer capability of the grid-side converter is limited, which causes a transient energy imbalance on the DC side and leads to an increase in the DC-link voltage. Similar DC-link voltage fluctuation issues during LVRT have been reported in PMSG-based wind energy systems [26]. After fault clearance, the DC-link voltage gradually returns to its rated value. It can be seen that, compared with PSO and OBO-PI, the proposed SG-PSO suppresses the DC-link voltage peak more effectively and accelerates the DC-link voltage recovery process. This indicates that the improvement of PCC voltage recovery achieved by SG-PSO is not obtained at the expense of DC-side energy stability. Instead, the proposed method can simultaneously improve AC-side voltage recovery and DC-side voltage stability.

Figure 9 shows the active and reactive power responses of the converter optimized by different algorithms. During the fault period, the PCC voltage drops, and the active power transfer capability of the grid-side converter is reduced; therefore, the active power decreases significantly. Meanwhile, the converter increases its reactive power output to support the PCC voltage. After fault clearance, the system gradually exits the reactive power support mode and returns to the active power tracking state. Compared with PSO and OBO-PI, the active power recovery process optimized by SG-PSO is smoother, and the oscillation amplitude during the reactive power decay process is smaller. This indicates

that the proposed method can effectively mitigate the transient impact caused by control mode switching during the LVRT recovery stage.

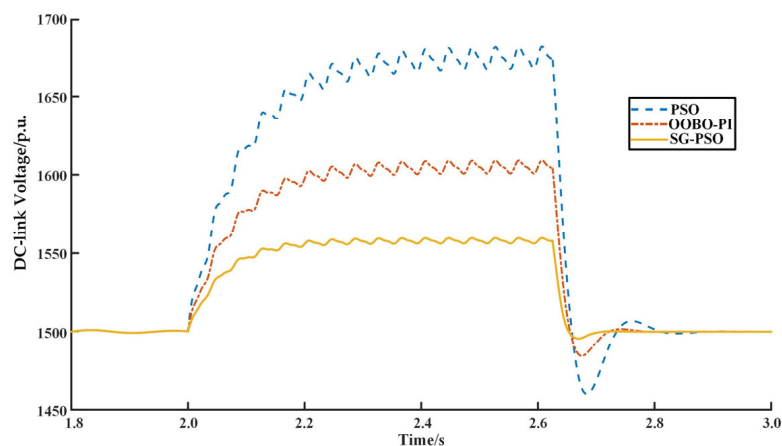


Figure 8. Comparison of DC-link voltage responses optimized by PSO, OBO-PI, and SG-PSO under SCR = 1.5.

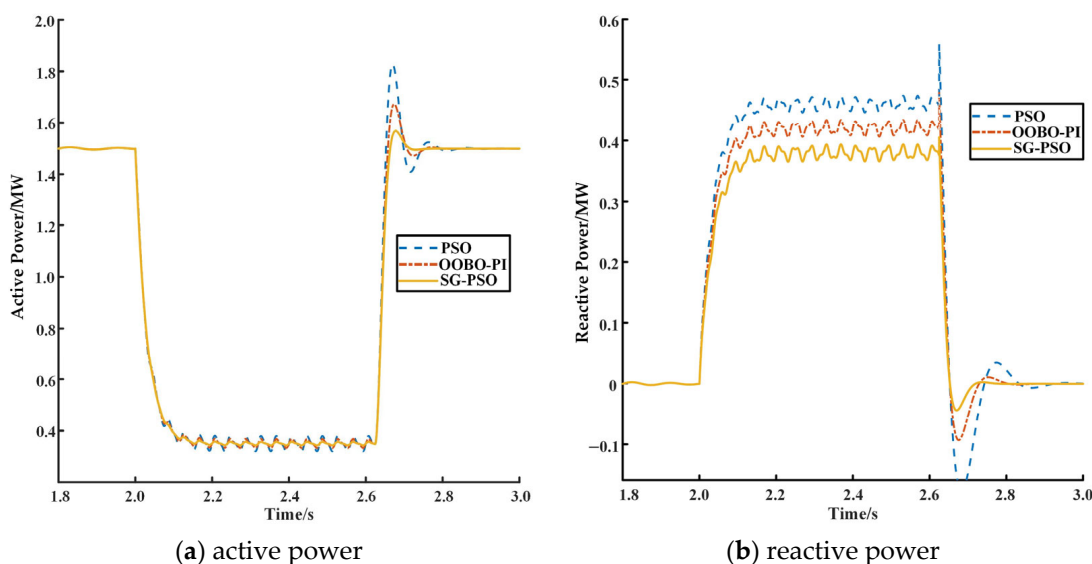


Figure 9. Active and reactive power responses optimized by PSO, OBO-PI, and SG-PSO under SCR = 1.5: (a) active power; (b) reactive power.

Table 4 quantitatively compares the transient recovery indices under different optimization algorithms. It can be observed that SG-PSO achieves lower PCC-voltage overshoot, shorter recovery time, lower DC-link voltage peak, and shorter DC-link settling time than PSO and OBO-PI under the same simulation and constraint settings. Specifically, SG-PSO reduces the PCC voltage overshoot to 1.4% and shortens the recovery time to 58 ms. Meanwhile, the DC-link voltage peak is reduced from 1681.8 V under PSO to 1559.8 V. These results demonstrate that the proposed method can not only improve PCC voltage recovery performance under weak grid conditions but can also effectively suppress DC-side voltage fluctuation, thereby enhancing the overall transient stability of the PMSG wind turbine during the LVRT recovery stage.

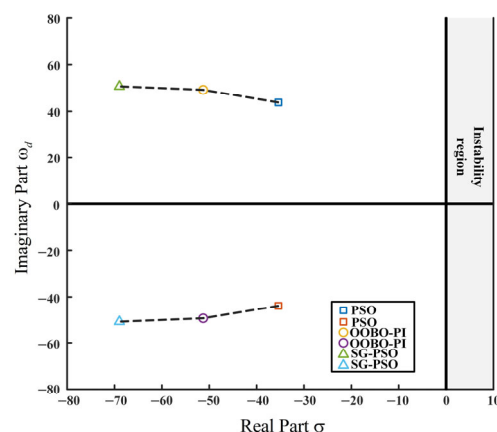
Table 4. Comparison of Overshoot and Settling Time Before and After Optimization.

Algorithm	PCC Overshoot/%	PCC Recovery Time/ms	DC-Link Peak/V	DC-Link Overshoot/%	DC-Link Settling Time/ms
PSO	7.9	113	1681.8	12.1	76.8
OOBO-PI	3.8	78	1609.1	7.3	18.2
SG-PSO	1.4	58	1559.8	4.0	9.8

4.2. Small-Signal Consistency Verification

To avoid evaluating the optimization effect solely based on time-domain waveforms, small-signal consistency verification is further performed because eigenvalue-based criteria can provide an independent assessment of the stability margin of PMSG-based wind power systems [21]. Specifically, the PI parameters optimized by PSO, OOBO-PI, and SG-PSO in Table 3 are substituted into the small-signal matrix A , forming the corresponding state matrices for the PSO, OOBO-PI, and SG-PSO cases, respectively. The eigenvalues of these matrices are then directly calculated. Subsequently, the pair of complex conjugate roots closest to the imaginary axis and dominant in the recovery process is selected as the dominant eigenvalue λ_{dom} . It should be emphasized that the dominant eigenvalues in this section are directly obtained from the small-signal matrix A , rather than being inversely derived from the time-domain overshoot and recovery time. Therefore, they can be used to independently verify the consistency between the dominant-mode analysis and the time-domain simulation results.

Figure 10 presents the distribution of the dominant eigenvalues calculated from the small-signal matrix A corresponding to different optimization algorithms. It can be observed that the dominant eigenvalues optimized by PSO are still close to the imaginary axis, indicating insufficient system damping and a slow transient attenuation rate after fault clearance. The dominant eigenvalues optimized by OOBO-PI shift leftward compared with those of PSO, indicating that the transient attenuation capability is improved to a certain extent. In contrast, the dominant eigenvalues optimized by SG-PSO move further into the left half-plane and exhibit a higher damping ratio, demonstrating that the proposed algorithm can effectively enhance system damping and transient recovery speed from the perspective of complex-frequency-domain pole reshaping.

**Figure 10.** Distribution of dominant eigenvalues optimized by PSO, OOBO-PI, and SG-PSO under SCR = 1.5.

Furthermore, the dominant eigenvalues directly obtained from the small-signal matrix A are substituted into the eigenvalue–time-domain index relationships established in Section 2.2 to calculate the damping ratio, predicted recovery time, and predicted overshoot.

The predicted results are then compared with the recovery time and overshoot extracted from the Simulink time-domain waveforms in Table 4, as summarized in Table 5.

Table 5. Comparison between small-signal prediction and nonlinear simulation results.

Algorithm	λ_{dom}	ζ	Predicted T_s/ms	Simulated T_s/ms	Error/%	Predicted $M_p/\%$	Simulated $M_p/\%$	Error/%
PSO	$-36.20 \pm j44.80$	0.6285	110.50	113	2.21	7.90	7.9	0.02
OOBO-PI	$-52.00 \pm j50.10$	0.7201	76.92	78	1.38	3.84	3.8	0.95
SG-PSO	$-69.50 \pm j51.30$	0.8046	57.55	58	0.77	1.42	1.4	1.26

Note: j denotes the imaginary unit in the complex eigenvalue expression.

As shown in Table 5, the recovery time and overshoot predicted by the dominant eigenvalues calculated from the small-signal matrix A are basically consistent with the nonlinear time-domain simulation results. Although certain deviations exist between the small-signal predictions and the Simulink results due to control mode switching, current limitation, and converter nonlinearities during LVRT, the variation trends remain consistent. Specifically, the dominant eigenvalues corresponding to PSO are closest to the imaginary axis, and both the predicted and simulated results show a longer recovery time and a larger overshoot. The dominant eigenvalues of OOBO-PI shift leftward, resulting in improved recovery performance. The dominant eigenvalues of SG-PSO are located farthest from the imaginary axis and have the largest damping ratio; therefore, both the predicted and simulated recovery times are the shortest, and the overshoot is the smallest. These results support the consistency of the established small-signal dominant-mode model and indicate that the dominant-eigenvalue-oriented PI parameter optimization has clear physical interpretability.

4.3. Adaptability Verification Under SCR = 2.5

To verify the adaptability of the proposed SG-PSO method under different grid strengths, the short-circuit ratio is further adjusted to SCR = 2.5, while the other simulation conditions remain unchanged. Under this operating condition, the SG-PSO algorithm is re-triggered to adaptively optimize the six-dimensional PI parameters, and the results are compared with those obtained under SCR = 1.5.

Table 6 lists the PI parameters optimized by SG-PSO under different SCR conditions. It can be observed that when SCR increases from 1.5 to 2.5, the grid strength is enhanced and the coupling effect between the PLL and the current loop is weakened. The algorithm can generate less conservative SCR-dependent PI parameter settings, thereby further improving the recovery speed while maintaining a sufficient stability margin.

Table 6. SG-PSO optimized PI parameters under different SCRs.

SCR	$K_{p,pll}$	$K_{i,pll}$	$K_{p,i}$	$K_{i,i}$	$K_{p,dc}$	$K_{i,dc}$
1.5	26.0	620	0.66	100	0.73	70
2.5	31.0	760	0.68	104	0.69	63

Figure 11 compares the PCC voltage recovery waveforms optimized by SG-PSO under different SCR conditions. When SCR = 1.5, the grid is weak, the machine–grid coupling is strong, and the system damping margin is relatively small. Therefore, the algorithm tends to adopt a more conservative parameter tuning strategy to prioritize the suppression of voltage overshoot and secondary oscillation. When SCR increases to 2.5, the grid voltage support capability is enhanced, and the machine–grid coupling effect is weakened. SG-PSO can adopt less conservative PI parameter settings while satisfying the

required damping constraint, thereby further shortening the voltage recovery time while maintaining a sufficient stability margin.

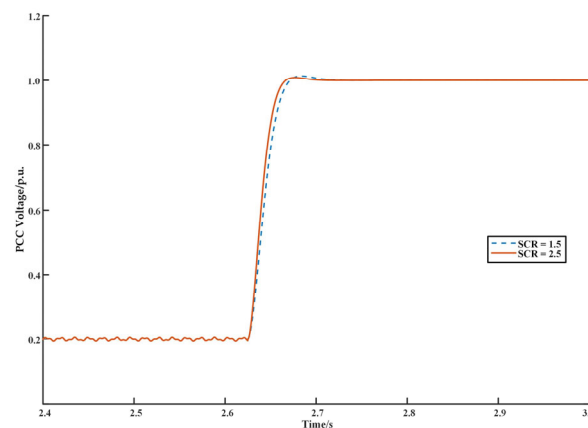


Figure 11. PCC voltage recovery waveforms optimized by SG-PSO under different SCRs.

Table 7 further presents the transient recovery indices under different SCR conditions. The results show that when SCR increases from 1.5 to 2.5, the PCC voltage overshoot decreases from 1.4% to 0.9%, and the recovery time is shortened from 58 ms to 46 ms. Meanwhile, the DC-link voltage peak and settling time are also further reduced. These results indicate that the proposed SG-PSO can generate SCR-dependent PI parameter settings according to the variation in grid strength. Under weak grid conditions, the method prioritizes damping enhancement and overshoot suppression, whereas under relatively stronger grid conditions, it appropriately improves the response speed, thereby achieving an adaptive balance between stability and rapidity.

Table 7. Comparison of optimized performance under different SCRs.

SCR	PCC Overshoot/%	PCC Recovery Time/ms	λ_{dom}	ζ
1.5	1.4	58	$-69.50 \pm j51.30$	0.8046
2.5	0.9	46	$-86.83 \pm j58.92$	0.8275

Note: j denotes the imaginary unit in the complex eigenvalue expression.

4.4. Robustness Verification Under Parameter Perturbations and Fault Variations

Robust FRT control has been investigated for PMSG-WT systems, highlighting the importance of maintaining stable recovery under disturbances and parameter variations [27]. To further verify the engineering applicability of the proposed SG-PSO method, robustness verification is carried out under parameter perturbations and fault variations. It should be noted that this section differs from the adaptability verification in Section 4.3. In this section, the PI parameter set optimized by SG-PSO under the nominal SCR = 1.5 condition is fixed, and no re-optimization is performed under different perturbation cases. This setting is adopted to examine whether the optimized parameter set still maintains satisfactory stability and dynamic performance under physical parameter deviations and fault condition variations.

Table 8 lists the robustness test cases. The considered perturbations include grid equivalent inductance variation, DC-link capacitance variation, filter inductance deviation, more severe voltage sag, and extended fault duration. These perturbations examine the robustness of the proposed method from several representative aspects, including grid strength, DC-side energy buffering capability, converter filter parameters, and fault severity.

Table 8. Robustness test cases.

Case	Perturbation Condition	Purpose
R0	Nominal condition	Benchmark case
R1	$L_g + 20\%$	Weaker grid condition
R2	$L_g - 20\%$	Relatively stronger grid condition
R3	$C - 20\%$	Reduced DC-side energy buffering capability
R4	$L_f + 10\%$	Filter parameter deviation
R5	Voltage sag to 0.1 p.u.	More severe voltage sag
R6	Fault duration extended to 1000 ms	Longer LVRT stress

Figure 12 shows the PCC voltage responses under different perturbation cases. It can be observed that although system parameters and fault conditions vary, the PCC voltage in all cases can recover to a stable operating state after fault clearance, and no sustained oscillation or secondary instability occurs. When the grid equivalent inductance increases or the fault depth becomes more severe, the overshoot and oscillation during PCC voltage recovery increase to some extent, but the system remains stable. This indicates that the PI parameters optimized by SG-PSO under the nominal weak grid condition have a certain robustness against grid strength variation and fault severity variation.

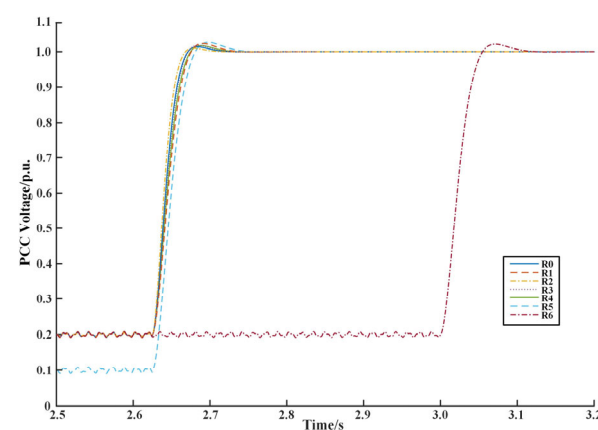
**Figure 12.** PCC voltage responses under different robustness test cases.

Figure 13 presents the DC-link voltage responses under different perturbation cases. It can be seen that when the DC-link capacitance decreases or the voltage sag becomes more severe, the DC-side energy imbalance is intensified, leading to a larger DC-link voltage fluctuation. Nevertheless, under all tested perturbation cases, the DC-link voltage can gradually return to the vicinity of its rated value after fault clearance, without sustained increase or instability. This indicates that the proposed SG-PSO method can maintain DC-side energy stability while improving PCC voltage recovery characteristics.

Table 9 quantitatively summarizes the transient recovery indices under different perturbation cases. It can be observed that under the tested parameter perturbations and fault variations, the PCC voltage overshoot, recovery time, and DC-link voltage peak remain within acceptable ranges, and the system can recover stably in all cases. These results demonstrate that the proposed SG-PSO method not only has good optimization performance under the nominal weak grid condition but also exhibits satisfactory robustness under the tested parameter deviations and fault-condition variations.

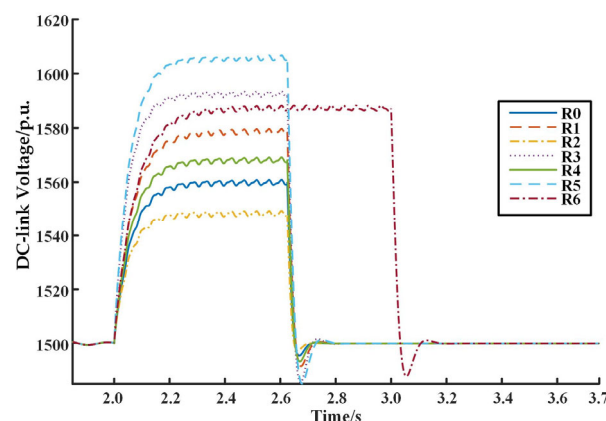


Figure 13. DC-link voltage responses under different robustness test cases.

Table 9. Quantitative robustness verification results.

Case	PCC Overshoot/%	PCC Recovery Time/ms	DC-Link Peak/V	Stability
R0	1.4	58	1559.8	Stable
R1	3.2	92	1586.4	Stable
R2	0.8	46	1544.2	Stable
R3	1.9	66	1612.6	Stable
R4	2.1	72	1574.8	Stable
R5	4.1	108	1628.5	Stable
R6	3.5	96	1608.7	Stable

4.5. Extended Robustness Evaluation

Although the robustness of the proposed SG-PSO method has been verified under parameter uncertainties, including filter inductance variation, DC-link capacitance variation, fault depth variation, and fault-duration variation, practical wind-power systems are also subject to operating-condition changes and non-ideal fault disturbances. Therefore, additional robustness tests are conducted in this subsection by considering wind-speed variations and asymmetrical fault conditions. These scenarios are selected because they represent common operating and disturbance conditions encountered in practical weak-grid wind-power integration systems.

4.5.1. Wind Speed Variation

To evaluate the influence of operating-condition variations, three representative wind-speed conditions (8 m/s, 10 m/s, and 12 m/s) are considered. The optimized controller parameters obtained using SG-PSO remain unchanged, and the system is subjected to the same LVRT event under $SCR = 1.5$. The corresponding PCC voltage recovery responses are compared to assess the adaptability of the proposed method to varying mechanical input conditions.

As shown in Figure 14, the voltage recovery characteristics under different wind-speed conditions remain highly consistent. The 8 m/s case exhibits a slightly slower recovery due to the reduced mechanical power input, while the 12 m/s case shows a marginally larger overshoot because of the increased energy transfer during the post-fault recovery process. Nevertheless, the differences among the three operating conditions are small, and all cases achieve stable voltage restoration within a short period. This indicates that the dominant recovery dynamics are mainly governed by the converter control loops rather than the mechanical subsystem, demonstrating the robustness of the proposed SG-PSO method against wind-speed variations.

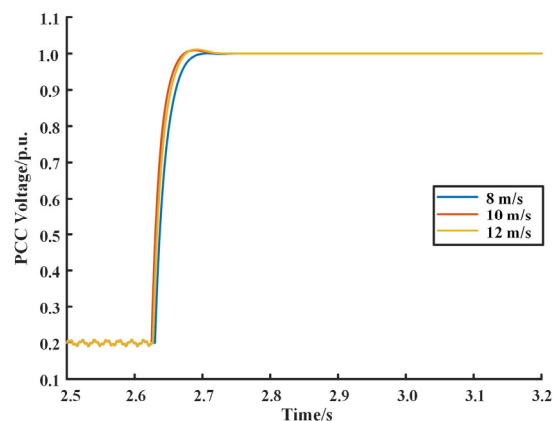


Figure 14. PCC voltage recovery responses under different wind-speed conditions.

4.5.2. Single-Phase Fault

To further investigate the performance of the proposed method under non-ideal fault conditions, a single-phase-to-ground fault is applied at the PCC. The fault is initiated at 2 s and cleared at 2.625 s. Compared with the three-phase short-circuit fault, the voltage sag caused by the single-phase fault is less severe, but it still introduces asymmetrical disturbance and additional coupling effects in the converter-grid system. The voltage recovery characteristics obtained using PSO, OBO-PI, and SG-PSO are compared to evaluate whether the dominant-mode-oriented optimization strategy remains effective under asymmetrical fault disturbances.

Figure 15 presents the PCC voltage recovery responses under a single-phase-to-ground fault. Compared with the three-phase short-circuit condition, the voltage sag is less severe, resulting in a milder disturbance to the converter control system. Consequently, all three optimization methods exhibit improved recovery performance. Nevertheless, the proposed SG-PSO method still achieves the fastest voltage restoration and the smallest overshoot, while the PSO-based controller exhibits the slowest recovery and the largest transient deviation. These results indicate that the dominant-mode-oriented optimization strategy remains effective under asymmetrical fault disturbances and maintains satisfactory robustness under representative operating and disturbance conditions.

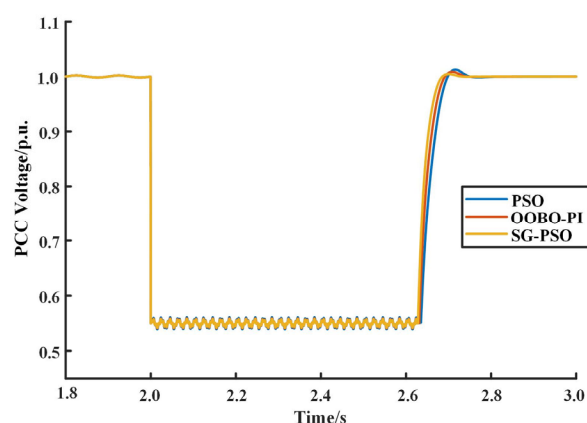


Figure 15. PCC voltage recovery responses under single-phase-to-ground fault.

4.6. Summary of Simulation Results

In summary, through algorithm comparison under the weak grid condition of $SCR = 1.5$, small-signal consistency verification, adaptability verification under $SCR = 2.5$, and robustness verification under parameter perturbations and fault variations, the following conclusions can be drawn. Compared with conventional PSO and the recently reported

OOBO-PI, the proposed SG-PSO can more effectively improve system damping, reduce PCC voltage overshoot, shorten the voltage recovery time after fault clearance, and suppress DC-link voltage fluctuation. Meanwhile, the small-signal prediction results show good consistency with the nonlinear time-domain simulation results, supporting the validity of the dominant-mode analysis model established in this paper. Furthermore, the extended robustness evaluations under wind-speed variations and single-phase fault disturbances further support the effectiveness of the proposed method under representative operating and disturbance conditions. The overall results demonstrate that the proposed method can maintain good transient stability performance under the tested grid-strength variations, system-parameter deviations, fault-condition variations, operating-condition changes, and asymmetrical fault disturbances.

5. Conclusions

This paper investigated the LVRT recovery dynamics of PMSG wind turbines connected to weak grids and proposed an SCR-adaptive SG-PSO method for coordinated PI parameter tuning. A transient recovery characteristic matrix A was established by considering the interactions among the PLL, the inner current loop, the DC-link voltage loop, and the grid-side inductance. Based on dominant-mode analysis and parameter root locus evolution, the influence mechanism of grid strength and PI parameters on the LVRT recovery process was clarified. The main conclusions are as follows:

- (1) The dominant-mode analysis shows that the decrease in SCR strengthens the coupling between the PLL and the inner current loop through PCC voltage distortion. This coupling reduces the damping margin of the dominant eigenvalues and moves them toward the imaginary axis, which explains the increased PCC voltage overshoot and secondary oscillations observed during the LVRT recovery stage. The root locus results further indicate that the PLL parameters have a strong destabilizing effect under weak-grid conditions, whereas the DC-link voltage-loop parameters provide stabilizing traction to improve post-fault energy recovery. In contrast, the inner current-loop parameters mainly contribute to local adjustment of the low-frequency dominant mode.
- (2) The proposed SG-PSO method incorporates SCR-adaptive damping constraints and normalized real-part sensitivity guidance into the PI tuning process. Instead of searching blindly in the full six-dimensional parameter space, the algorithm dynamically identifies the PI parameters that have the greatest influence on the dominant eigenvalue and updates them preferentially. This mechanism improves the physical interpretability of the optimization process and enables the parameter tuning strategy to adapt to different grid strengths.
- (3) Comparative simulations under $SCR = 1.5$ demonstrate that SG-PSO achieves better evaluated LVRT recovery indices than PSO and OOBO-PI under the same simulation and constraint settings. The PCC voltage overshoot is reduced to 1.4%, and the recovery time is shortened to 58 ms. Meanwhile, the DC-link voltage peak is reduced to 1559.8 V, indicating that the improvement in PCC voltage recovery is not achieved at the expense of DC-side stability. The dominant eigenvalues obtained from the small-signal model are consistent with the nonlinear simulation results, confirming the validity of the proposed dominant-mode-based optimization framework.
- (4) The adaptability verification under $SCR = 2.5$ shows that SG-PSO can further shorten the PCC voltage recovery time to 46 ms while maintaining a low overshoot of 0.9%. This result indicates that the proposed method can prioritize damping enhancement under weak-grid conditions and adopt less conservative PI parameter settings when the grid strength increases. In addition, robustness tests under grid inductance varia-

tion, DC-link capacitance reduction, filter inductance deviation, deeper voltage sag, extended fault duration, wind-speed variations, and single-phase-to-ground fault disturbance show that the optimized parameters can maintain stable recovery in the tested cases under the tested parameter uncertainties, operating-condition changes, and asymmetrical fault disturbances.

The present study mainly focuses on the LVRT recovery mechanism and PI-parameter tuning of PMSG wind turbines under weak-grid conditions. The proposed small-signal model is derived under the assumptions that filter resistance and grid resistance are neglected, and the main comparative verification is conducted under balanced three-phase fault conditions. Although wind-speed variation and single-phase-to-ground fault cases are further included to evaluate the robustness of the proposed method under representative operating-condition changes and asymmetrical disturbances, broader practical scenarios still require further investigation. Future work will extend the proposed framework to two-phase faults, voltage imbalance, harmonic distortion, current saturation, and wider mechanical power variations. In addition, comprehensive statistical evaluations based on multiple independent optimization runs and hardware-in-the-loop or experimental validation will be conducted to further verify the repeatability and engineering applicability of the proposed SG-PSO method.

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Nomenclature

SCR	Short-circuit ratio
LVRT	Low-voltage ride-through
PMSG	Permanent magnet synchronous generator
PLL	Phase-locked loop
PCC	Point of common coupling
PI	Proportional–integral controller
PSO	Particle swarm optimization
SG-PSO	Sensitivity-guided particle swarm optimization
OOBO-PI	One-to-one-based optimizer tuned PI controller
FCS-MPC	Finite-control-set model predictive control
V_{dc}	DC-link voltage
$V_{pcc,d}, V_{pcc,q}$	dq-axis components of PCC voltage
i_d, i_q	dq-axis converter output currents
L_f	Filter inductance
L_g	Grid equivalent inductance
θ_g	Grid voltage phase angle
θ_{pll}	PLL output phase angle
Δx	Small-signal state vector

A	Transient recovery characteristic matrix
λ_{dom}	Dominant eigenvalue
σ	Real part of the dominant eigenvalue
ω_d	Imaginary part of the dominant eigenvalue
ζ	Damping ratio
T_s	Settling time
M_p	Overshoot
Θ	Vector of PI control parameters
$S_{\sigma,j}$	Normalized real-part sensitivity of the j-th PI parameter
Ω_{active}	Active parameter set selected by sensitivity ranking

Appendix A. Derivation of the State-Space Matrix

Appendix A provides the detailed algebraic derivation of the transient recovery characteristic matrix A introduced in Section 2.1. To remain consistent with the modeling assumptions in the main text, the filter resistance and grid line resistance are neglected, and only the effects of the filter inductance L_f and the grid equivalent inductance L_g on the small-signal dynamics are considered. Variables at the steady-state operating point are denoted by the subscript “0”. The state vectors adopted in the main text are defined as:

$$\begin{cases} \Delta x_c = [\Delta i_d, \Delta i_q, \Delta \phi_d, \Delta \phi_q]^T \\ \Delta x_v = [\Delta V_{dc}, \Delta \phi_{vdc}]^T \\ \Delta x_{pll} = [\Delta \zeta_{pll}, \Delta \theta_{pll}]^T \end{cases} \quad (\text{A1})$$

The overall state vector of the system is written as:

$$\Delta x = [\Delta x_c^T, \Delta x_v^T, \Delta x_{pll}^T]^T \quad (\text{A2})$$

It should be noted that $\Delta \zeta_{pll}$ is uniformly used to denote the internal integral state of the PLL, while Δx_{pll} is used only as the PLL state sub-vector to avoid symbol confusion.

Appendix A.1. Derivation of the Block Matrix for the Current Subsystem

In the dq rotating reference frame, considering the converter output filter inductance L_f and neglecting the filter resistance and grid line resistance, the small-signal equations of the current subsystem can be obtained according to Kirchhoff’s voltage law:

$$\begin{cases} L_f \frac{d\Delta i_d}{dt} = \Delta v_{md} - \Delta V_{pcc,d} + \omega_0 L_f \Delta i_q \\ L_f \frac{d\Delta i_q}{dt} = \Delta v_{mq} - \Delta V_{pcc,q} - \omega_0 L_f \Delta i_d \end{cases} \quad (\text{A3})$$

where Δv_{md} and Δv_{mq} are the perturbations of the converter bridge-arm output voltage in the d- and q-axes, respectively, and $\Delta V_{pcc,d}$ and $\Delta V_{pcc,q}$ are the perturbations of the PCC voltage in the d and q-axes, respectively.

The current inner loop of the grid-side converter adopts PCC voltage feedforward and cross-decoupling control. The bridge-arm voltage commands can be expressed as:

$$\begin{cases} \Delta v_{md} = K_{p,i}(\Delta i_{dref} - \Delta i_d) + K_{i,i}\Delta \phi_d - \omega_0 L_f \Delta i_q + \Delta V_{pcc,d} \\ \Delta v_{mq} = K_{p,i}(\Delta i_{qref} - \Delta i_q) + K_{i,i}\Delta \phi_q + \omega_0 L_f \Delta i_d + \Delta V_{pcc,q} \end{cases} \quad (\text{A4})$$

The integral states of the current PI controllers satisfy:

$$\begin{cases} \frac{d\Delta \phi_d}{dt} = \Delta i_{dref} - \Delta i_d \\ \frac{d\Delta \phi_q}{dt} = \Delta i_{qref} - \Delta i_q \end{cases} \quad (\text{A5})$$

After substituting the bridge-arm voltage commands into the physical equations of the current subsystem, the PCC voltage feedforward terms and cross-decoupling terms are eliminated under the adopted decoupled current-control structure. Thus:

$$\begin{cases} \frac{d\Delta i_d}{dt} = \frac{1}{L_f} \left[-K_{p,i}\Delta i_d + K_{p,i}\Delta i_{dref} + K_{i,i}\Delta \phi_d \right] \\ \frac{d\Delta i_q}{dt} = \frac{1}{L_f} \left[-K_{p,i}\Delta i_q + K_{p,i}\Delta i_{qref} + K_{i,i}\Delta \phi_q \right] \end{cases} \quad (A6)$$

During the LVRT recovery stage, the system switches from the reactive power support mode during the fault to the active power tracking mode. In this stage, the active current command is generated by the DC-link voltage outer loop ($\Delta i_{dref} = -K_{p,dc}\Delta V_{dc} + K_{i,dc}\Delta \phi_{vdc}$), and the reactive current command perturbation is set as $\Delta i_{qref} = 0$. Therefore, the small-signal dynamics of the current inner-loop subsystem can be written as: $\Delta \dot{x}_c = A_{cc}\Delta x_c + A_{cv}\Delta x_v$, where A_{cc} represents the self-dynamics of the current inner loop, and A_{cv} represents the influence of the DC-link voltage outer loop on the active current command of the current inner loop.

$$\frac{d\Delta V_{dc}}{dt} = a_{vd}\Delta i_d + a_{vq}\Delta i_q + a_{vv}\Delta V_{dc} \quad (A7)$$

$$A_{cc} = \begin{bmatrix} -\frac{K_{p,i}}{L_f} & 0 & \frac{K_{i,i}}{L_f} & 0 \\ 0 & -\frac{K_{p,i}}{L_f} & 0 & \frac{K_{i,i}}{L_f} \\ -1 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 \end{bmatrix} \quad (A8)$$

$$A_{cv} = \begin{bmatrix} -\frac{K_{p,i}K_{p,dc}}{L_f} & \frac{K_{p,i}K_{i,dc}}{L_f} \\ 0 & 0 \\ -K_{p,dc} & K_{i,dc} \\ 0 & 0 \end{bmatrix} \quad (A9)$$

Appendix A.2. Derivation of the Block Matrix for the DC-Link Voltage Subsystem

The DC-link voltage dynamics are determined by the energy balance between the DC-side input power and the grid-side output power. When converter losses are neglected, the DC-link capacitor satisfies:

$$V_{dc}C\frac{dV_{dc}}{dt} = P_{in} - P_g \quad (A10)$$

where P_{in} denotes the power injected into the DC link from the machine side, and P_g denotes the active power delivered to the AC side by the grid-side converter. The grid-side active power can be expressed as:

$$P_g = \frac{3}{2} (V_{pcc,d}i_d + V_{pcc,q}i_q) \quad (A11)$$

By performing small-signal linearization around the steady-state operating point after fault clearance, the following equation can be obtained:

$$CV_{dc0}\frac{d\Delta V_{dc}}{dt} = \Delta P_{in} - \Delta P_g \quad (A12)$$

where:

$$\Delta P_g = 3/2 \left(V_{pcc,d0}\Delta i_d + V_{pcc,q0}\Delta i_q + i_{d0}\Delta V_{pcc,d} + i_{q0}\Delta V_{pcc,q} \right) \quad (A13)$$

During the LVRT recovery stage, to highlight the dominant coupling relationship between the DC-link voltage outer loop and the current inner loop, the above equation can be rearranged into the following linear form:

$$\frac{d\Delta V_{dc}}{dt} = a_{vd}\Delta i_d + a_{vq}\Delta i_q + a_{vv}\Delta V_{dc} \quad (\text{A14})$$

where a_{vd} , a_{vq} , and a_{vv} are linearized coefficients determined by the steady-state operating point and system parameters. They characterize the effects of the d-axis current, q-axis current, and DC-link voltage perturbations on the DC-side energy balance, respectively. The integral state of the DC-link voltage PI controller satisfies:

$$\frac{d\Delta\phi_{vdc}}{dt} = -\Delta V_{dc} \quad (\text{A15})$$

Therefore, the DC-link voltage outer-loop subsystem can be written as:

$$\Delta \dot{x}_v = A_{vc}\Delta x_c + A_{vv}\Delta x_v \quad (\text{A16})$$

where A_{vc} represents the feedback effect of current perturbations on the DC-link voltage, and A_{vv} represents the self-dynamics of the DC-link voltage outer loop.

$$A_{vc} = \begin{bmatrix} a_{vd} & a_{vq} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (\text{A17})$$

$$A_{vv} = \begin{bmatrix} a_{vv} & 0 \\ -1 & 0 \end{bmatrix} \quad (\text{A18})$$

Appendix A.3. Derivation of the PLL Machine–Grid Cross-Coupling Matrix A_{pc}

The input of the PLL is the q-axis component of the PCC voltage in the control reference frame. The PLL adjusts its output phase angle to make this q-axis voltage approach zero, thereby achieving synchronization with the grid voltage. The internal integral state of the PLL is uniformly denoted as $\Delta\zeta_{pll}$, and the output phase-angle perturbation of the PLL is uniformly denoted as $\Delta\theta_{pll}$. Therefore, the small-signal dynamics of the PLL can be written as:

$$\begin{cases} \frac{d\Delta\zeta_{pll}}{dt} = \Delta V_{pcc,q}^c \\ \frac{d\Delta\theta_{pll}}{dt} = K_{p,pll}\Delta V_{pcc,q}^c + K_{i,pll}\Delta\zeta_{pll} \end{cases} \quad (\text{A19})$$

where ΔV_{pll}^c is the small-signal perturbation of the q-axis PCC voltage component in the control reference frame. Under weak grid conditions, the grid equivalent inductance L_g is relatively large. Current perturbations generate significant voltage perturbations across the grid equivalent inductance, resulting in PCC voltage distortion. Considering that the infinite grid voltage perturbation is zero, namely, $\Delta V_{g,q} = 0$, the q-axis PCC voltage perturbation can be expressed as:

$$\Delta V_{pcc,q} = L_g \frac{d\Delta i_q}{dt} + \omega_0 L_g \Delta i_d \quad (\text{A20})$$

By substituting $d\Delta i_q/dt$ from Appendix A.1 into the above equation, the current derivative term can be eliminated:

$$\Delta V_{pcc,q} = L_g \left[-\frac{K_{p,i}}{L_f} \Delta i_q + \frac{K_{i,i}}{L_f} \Delta\phi_q \right] + \omega_0 L_g \Delta i_d \quad (\text{A21})$$

In addition, due to the phase-angle deviation between the control reference frame and the actual system reference frame, the q-axis PCC voltage perturbation in the control reference frame can be approximated as:

$$\Delta V_{pcc,q}^c = \Delta V_{pcc,q} - V_{pcc,d0} \Delta \theta_{pll} \quad (A22)$$

Therefore:

$$\Delta V_{pcc,q}^c = \omega_0 L_g i_d - L_g \frac{K_{p,i}}{L_f} i_q + L_g \frac{K_{i,i}}{L_f} \Delta \phi_q - V_{pcc,d0} \Delta \theta_{pll} \quad (A23)$$

Substituting the above expression into the PLL dynamic equations gives the partitioned state equation of the PLL subsystem:

$$\Delta \dot{x}_{pll} = A_{pc} \Delta x_c + A_{pp} \Delta x_{pll} \quad (A24)$$

where A_{pp} represents the self-dynamics of the PLL, and A_{pc} represents the coupling channel through which current perturbations act on the PLL via PCC voltage distortion under weak grid conditions.

$$A_{pc} = \begin{bmatrix} \omega_0 L_g & -L_g \frac{K_{p,i}}{L_f} & 0 & L_g \frac{K_{i,i}}{L_f} \\ K_{p,pll} \omega_0 L_g & -K_{p,pll} L_g \frac{K_{p,i}}{L_f} & 0 & K_{p,pll} L_g \frac{K_{i,i}}{L_f} \end{bmatrix} \quad (A25)$$

$$A_{pp} = \begin{bmatrix} 0 & -V_{pcc,d0} \\ K_{i,pll} & -K_{p,pll} V_{pcc,d0} \end{bmatrix} \quad (A26)$$

It can be seen from A_{pc} that the grid equivalent inductance L_g directly participates in the coupling channel between the PLL and the current inner loop. When SCR decreases, L_g increases, and the coupling coefficients in A_{pc} are strengthened accordingly. As a result, current perturbations are more easily transferred to the PLL input, causing the dominant eigenvalues to move toward the imaginary axis.

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