



Comparison of Oscillation Optimization Strategies for MMC-HVDC Based on Meta-heuristic Algorithms

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Abstract- This paper elucidates the oscillation issues in offshore wind farms employing modular multilevel converter -high-voltage direct current (MMC-HVDC) transmission systems. Initially, a small-signal model was constructed, integrating sub-module capacitor triple harmonic components and control link delays. Oscillation modes and their origins were elucidated through the analysis of participation factors and eigenvalues, facilitating the selection of controller parameters. Subsequently, the DBO(dung beetle optimization) algorithm was subsequently augmented with chaotic mapping, spiral search strategies, Levy flights, and t-distribution-based perturbation strategies, collectively termed the TDBO algorithm. A strategy for modulating controller parameters to reduce oscillation risks in the flexible direct current system was proposed. Finally, Comparative performance analysis of several algorithms was conducted using benchmark test functions and the small-signal model, culminating in the identification of the most efficacious algorithm for addressing this specific engineering challenge.

Keywords MMC-HVDC system, small-signal model, controller parameter optimization, meta-heuristic algorithms.

Nomenclature

J	inertia of PMSG	L_{WF}, L_{GS}	WFMMC and GSMMC equivalent inductance
ω	angular velocity	K_{pld_WF}, K_{ild_WF} K_{plq_WF}, K_{ilq_WF}	dq-axis internal loop Kp and Ki value of WFMMC controllerr
T_M, T_e	mechanical torque and electromagnetic torque of PMSG	X_{10}, X_{11}	dq-axis internal loop integral link output of WFMMC controller
D	damping coefficient of PMSG	I_{dref_GS}, I_{qref_GS}	given value of GSMMC current dq-axis component
ω_M, ω_{ref_M}	rotor angular velocity of PMSG and its set value	V_{dc_GS}, V_{dcref_GS}	MMC DC line voltage and its set value

$V_{d_M}, V_{q_M},$ V_{dref_M}, V_{qref_M}	dq-axis components of MSC voltage and its set value	$Q_{_GS}, Q_{ref_GS}$	GSMC reactive power and its set value
R_a	equivalent resistance of PMSG stator	K_{pVdc_GS}, K_{iVdc_GS} K_{pQ_GS}, K_{iQ_GS}	dq-axis outer loop Kp and Ki value of GSMC controller
$I_{d_M}, I_{q_M},$ I_{dref_M}, I_{qref_M}	dq-axis component of MSC current and its set value	X_{15}, X_{16}	output of dq-axis outer ring integral link of GSMC controller
L_{d_M}, L_{q_M}	dq-axis component of stator inductance of generator set	V_{dref_GS}, V_{qref_GS}	GSMC voltage dq-axis component reference value
ψ	generator set permanent magnet magnetic chain	I_{dm_GS}, I_{qm_GS}	current dq-axis component of GSMC after time delay
$K_{p\omega_M}, K_{i\omega_M}$	MSC controller d-axis outer loop Kp and Ki values	V_{sd_GS}, V_{sq_GS}	GSMC voltage dq-axis component
X_1	output of MSC q-axis outer loop integral component	K_{pld_GS}, K_{ild_GS} K_{plq_GS}, K_{ilq_GS}	dq-axis internal loop Kp and Ki value of GSMC controller
$K_{pld_M}, K_{ild_M},$ K_{plq_M}, K_{ilq_M}	MSC controller dq-axis internal loop Kp and Ki values	X_{17}, X_{18}	dq-axis internal loop integral link output of GSMC controller
X_2, X_3	dq-axis internal loop integral link outputs of MSC controller	$K_{pcir_MMC},$ K_{icir_MMC}	CCSC controller Kp and Ki values
$K_{pQ_G}, K_{iQ_G},$ K_{pVdc_G}, K_{iVdc_G}	GSC controller dq-axis outer loop Kp and Ki values	$I_{cirdref}, I_{cirqref}$	given values of binary-frequency circulation dq-axis component of MMC
Q_G, Q_{ref_G}	GSC reactive power and its set value	k_{pPLL}, k_{iPLL}	PLL Kp and Ki values
V_{dc_G}, V_{dcref_G}	PMSG intermediate capacitor voltage and its set value	X_{12}, X_{19}	WFMMC and GSMC PLL integral link output
X_4, X_5	dq-axis outer loop integral link outputs of GSC controller	X_{13}, X_{20}	d-axis integral component outputs of WFMMC and GSMC CCSC controllers
$V_{d_G}, V_{q_G}, V_{dref_G},$ V_{qref_G}	GSC voltage dq-axis component and its set values	X_{14}, X_{21}	q-axis integral component outputs of WFMMC and GSMC CCSC controllers
$I_{d_G}, I_{q_G}, I_{dref_G},$ I_{qref_G}	GSC current dq-axis component and its set values	V_{sd_MMC}, V_{sq_MMC}	MMC bus-bar voltage dq-axis component
ω_G	GSC electrical angular velocity	U_m	PCC point voltage amplitude
L_G	GSC inductance	θ_0	initial phase angle of the PLL

$K_{pld_G}, K_{ild_G}, K_{plq_G}, K_{ilq_G}$	GSC controller dq-axis internal loop Kp and Ki values	θ_{MMC}	MMC phase-locked ring phase angle
X_6, X_7	dq-axis internal loop integral link output of GSC controller	λ	the characteristic root of the matrix
C_{MG}	PMSG intermediate capacitor	α, β	the real and imaginary part of the eigenvalue
P_M, P_G	MSC and GSC output active power	ξ	the characteristic root damping ratio
Q_M, Q_G	MSC and GSC output reactive power	p_{ki}	the oscillation participation factors
C_{sm}, V_{csm}	MMC submodule capacitance and its voltage	ϕ_{ki}, ψ_{ki}	the left and right eigenvectors of the matrix
$V_{csm0}, V_{csm1}, V_{csm2}, V_{csm3}$	MMC submodule voltage DC, fundamental frequency, second harmonic, and third harmonic components	a	the adjustment factor for the damping ratio portion of the objective function
I_{dc_MMC}	MMC DC current	b	the penalty function xiang in which the eigenroot of the objective function is in the positive and real part
V_{d_MMC}, V_{q_MMC}	MMC voltage dq-axis component	X_t	the position of individuals in the t iteration of the optimization algorithm
I_{d_MMC}, I_{q_MMC}	MMC current dq-axis component	X^b	the current optimal position of the optimization algorithm individual
V_{dc_MMC}	MMC DC voltage	Ub^*, Lb^*	the upper and lower bounds of the individual
V_{cird}, V_{cirq}	CCSC output voltage dq-axis component	l, b_1, b_2	the parameter in the algorithm, a random number between [-1, 1]
$V_{csm1d}, V_{csm1q}, V_{csm2d}, V_{csm2q}, V_{csm3x}, V_{csm3y}$	fundamental, second, and third harmonic components of MMC submodule voltage in dq-axis	NGO	northern goshawk optimization
I_{cird}, I_{cirq}	binary-frequency circulation dq-axis component of MMC	PMSG	permanent magnet synchronous generator
L_{arm}	MMC bridge arm inductance	MSC	machine-side converter
N	number of MMC submodules	GSC	grid-side converter
R_{eq}, L_{eq}	MMC equivalent resistance and inductance	WFMMC	wind farm modular multilevel converter
I_{dref_WF}, I_{qref_WF}	given values of WFMMC current dq-axis component	GSMC	grid-side modular multilevel converter
V_{dref_WF}, V_{qref_WF}	given values of WFMMC voltage dq-axis component	TDBO	improved dung beetle optimization
V_{sdm_WF}, V_{sqm_WF}	WFMMC voltage dq-axis component after time delay	MMC-HVDC	modular multilevel converter high voltage direct current transmission

$K_{pVd_WF}, K_{iVd_WF}, K_{pVq_WF}, K_{iVq_WF}$	dq-axis outer loop Kp and Ki values of WFMMC controller	GWO	grey wolf optimization
X_8, X_9	dq-axis outer integral link output of WFMMC controller	PSO	particle swarm optimization
$V_{cdref_WF}, V_{cqref_WF}$	reference value of voltage dq-axis component of WFMMC	WOA	whale optimization algorithm
I_{dm_WF}, I_{qm_WF}	WFMMC current dq-axis component after time delay	DBO	dung beetle optimization
$\omega_{MMC}, \omega_{WF}, \omega_{GS}$	WFMMC and GSMMC electrical angular speed	SSA	sparrow search algorithm

1. Introduction

MMC-HVDC is increasingly recognized as an optimal solution for large-scale grid connection and long-distance transmission of new energy [1]. The modular architecture of MMC-HVDC enhances system flexibility and reliability, offering significant benefits such as low harmonic distortion, minimal current and voltage fluctuations, and elevated efficiency. Additionally, its superior current control capabilities and rapid dynamic response are crucial for fault management and adaptability in the power system modifications [2-3]. It is particularly prevalent in the transmission of offshore wind power. However, operational experience from various MMC-HVDC projects has revealed stability issues, predominantly oscillations induced by the grid connections of new energy sources using MMC technology [4-5]. A notable occurrence during the commissioning process of the Zhangbei wind power project in China was the detection of a secondary synchronous oscillation of around 44Hz [6]. Such oscillations pose a threat to system stability and can precipitate extensive power disruptions. To mitigate these oscillations in MMC-HVDC systems, three principal strategies are recommended: integration of filtering devices [7], enhancement of control structures [8], and optimization of controller parameters[9]. Compared to the first two methods, optimization of controller parameters is particularly advantageous due to the ease of parameter adjustment, elimination of additional control strategies, and its substantial applicability in engineering. Currently, adjustment of controllers in MMC-HVDC systems predominantly depends on experimental tuning methods. This approach, however, is challenged by the numerous parameters in the grid-connected system and the substantial time required to effectively suppress oscillations in the MMC-HVDC system.

To address the grid stability issues in MMC-HVDC systems, many researchers have conducted related studies. Reference [10] develops a comprehensive model of the MMC converter to analyze its internal dynamics. Reference [11] identifies critical variables contributing to oscillation modes in the direct-drive wind farm integrated with the MMC-HVDC using eigenvalue analysis, a methodology also

applied to HVDC studies in reference [12]. Reference [13] studies the impact of variations in grid impedance and control parameters of the phase-locked loop (PLL) on the overall system stability based on impedance models. However, this approach primarily adjusts individual controller parameters without considering the system as a whole. Artificial intelligence-based parameter optimization methods offer a holistic adjustment of the global parameters of the system, reducing reliance on manual parameter tuning. Various meta-heuristic algorithms have proven effective across different domains in power system and engineering practices [14-15], including optimization configuration of new energy power plants [16], microgrid scheduling [17], Maximum Power Point Tracking (MPPT) control of photovoltaics [18-20], optimization of PI controller parameters [21]. For instance, Reference [22] uses GWO to assess optimal strategies for reconstruction, distributed generation and parallel capacitor group deployment in the distribution system. The SSA is utilized in reference [23] to optimize the wind farm layout, thereby enhancing wind field efficiency. Reference [24] introduces the use of the particle swarm optimization algorithm for optimizing gas metal arc welding parameters. Reference [25] combines particle swarm optimization with fuzzy logic control to devise a maximum power point tracking control scheme for photovoltaic systems. Additionally, References [26] and [27] discuss the deployment of fractional-order fuzzy PID controllers and fuzzy fractional PDμ+I controllers in permanent magnet DC motor-driven wire feeder systems, optimized through particle swarm optimization algorithms. These studies demonstrate the efficacy of intelligent optimization algorithms in boost in control performance and supporting the automation and intelligence of engineering systems. In recent years, many groups intelligent algorithms have emerged, including widely recognized GWO [28], WOA [29], etc. Inspired by the social behavior of dung beetles, the newly devised Dung Beetle Optimization algorithm (DBO) has demonstrated superior performance, as demonstrated in reference [30]. Subsequent research has leveraged and refined this model to tackle various problems. In reference [31], DBO algorithm utilizes effective strategies such as good point set population initialization, nonlinear convergence factor adjustment, and adaptive Gaussian-Cauchy mutation techniques to evade

local optima. Furthermore, An IDBO algorithm integrating Levy flight strategy, a t-distribution disturbance strategy and a multiple group mechanism [32]. Collectively, these enhancements foster greater population diversity, facilitate DBO algorithm get rid of local extreme value, and enhance the global optimization ability .

However, in the domain of optimizing HVDC controller parameters, many studies predominantly employ the PSO algorithm. However, there has been limited exploration into newer meta heuristic algorithms that have emerged in recent years. The "No Free Lunch" theorem indicates that no singular algorithm is universally applicable across all engineering problems [33]. There is a conspicuous scarcity of comparative analyses regarding the efficacy of meta-heuristic algorithms in mitigating MMC-HVDC oscillations. This paper endeavors to delineate a rapid and accurate suppression strategy for oscillations in offshore direct-drive wind farms integrated with MMC-HVDC systems, thereby addressing the deficiencies observed in extant research through the following approaches:

(1) Establishment of a small signal model that incorporates the triple frequency component of the sub-module capacitor and the control link delay offshore wind farm MMC-HVDC system. This model, predicated upon divergent dq rotation coordinate system conversion, facilitates the establishment of an interface model between the wind farm and the MMC system to verify the accuracy and practicability of the small signal model.

(2) Analysis of the dynamic characteristics of offshore wind farm through MMC-HVDC system. According to the two evaluation indexes of participation factor and feature value, various oscillation modes—both intrinsic to the MMC system and resultant from interactions between wind farm and MMC system—are identified. Optimal controller parameters were selected according to the participation factors.

(3) DBO is enhanced through the integration of chaos mapping, spiral search strategy, Levy flight, and t distribution variation strategy. An optimization objective function, predicated on eigenvalues and damping ratios, is formulated to augment the stability of the grid-connected system. A comparative analysis of the performance of GWO, SSA, WOA, NGO, DBO, and TDBO under steady-state conditions is conducted. Subsequently, the optimally selected algorithm is applied to optimize the MMC-HVDC grid-connected system under unstable conditions, confirming the effectiveness of the proposed strategy.

2. MMC-HVDC SmallSignal Model

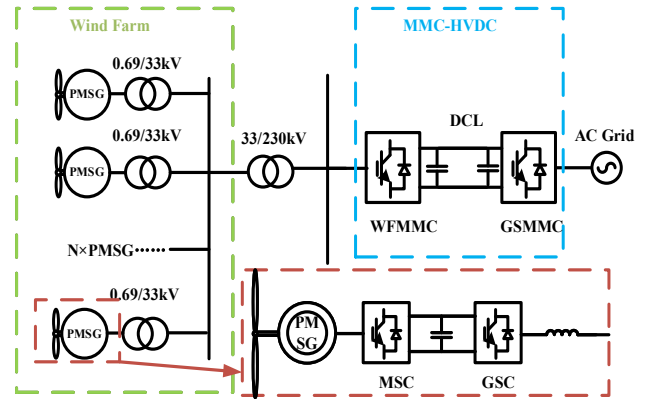


Fig.1. Wind Power Integration Topology Diagram via MMC-HVDC

Fig. 1 depicts the structure of the MMC-HVDC integrated system, optimized for direct-drive wind farms. The wind farm comprises multiple identical direct-drive wind turbines. The electrical output from these turbines is channeled into the AC bus via generator-side transformers, subsequently interfacing with the MMC-HVDC system via step-up transformers. Finally, the electrical energy, modulated by the WFMSC and GSC of the MMC-HVDC system, is then assimilated into the AC grid.

2.1. PMSG Model

The impeller converts the wind energy, converting it into mechanical energy, which is then transformed into electromagnetic power by the generator. The machine side converter and the network side converter are equipped with independent vector control system for control. The machine side converter, directly connected to the permanent magnet synchronous generator, is modulated by the generator output. This modulation produces pulse signals, facilitating the direct manipulation of current components on the d-axis and q-axis, thus adjusting the output electromagnetic torque of the generator control system. The fan is model by PMSG using axle line single mass block model. Expression, such as Eq. (1):

$$J \frac{d\omega_M}{dt} = T_M - T_e - D(\omega_M - \omega_{ref_M}) \quad (1)$$

With reference to the rotating magnetic field of the permanent magnet synchronous generator rotor, the stator voltage and current takes the motor convention. Stator winding voltage expression in dq synchronous rotation coordinate system such as Eq. (2):

$$\begin{cases} V_{d_M} = R_a I_{d_M} + L_{d_M} \frac{dI_{d_M}}{dt} - \omega_M L_{q_M} I_{q_M} \\ V_{q_M} = R_a I_{q_M} + L_{q_M} \frac{dI_{q_M}}{dt} + \omega_M L_{d_M} I_{d_M} + \psi \omega_M \end{cases} \quad (2)$$

The MSC uses the rotor magnetic field-oriented vector control, order $I_{dref_M}=0$, to achieve the maximum torque / current control.

MSC angular velocity outer loop control equations such as Eq. (3):

$$\begin{cases} I_{qref_M} = \left(K_{p\omega_M} + \frac{K_{i\omega_M}}{s} \right) (\omega_M - \omega_{ref_M}) \\ X_1 = \frac{K_{i\omega_M}}{s} (\omega_M - \omega_{ref_M}) \end{cases} \quad (3)$$

The MSC internal loop dynamics as in Eq. (4):

$$\left\{ \begin{aligned} V_{dref_M} &= - \left(K_{pld_M} + \frac{K_{ild_M}}{S} \right) (I_{dref_M} - I_{d_M}) \\ &\quad + \omega_M L_{q_M} I_{q_M} \\ V_{qref_M} &= - \left(K_{plq_M} + \frac{K_{ilq_M}}{S} \right) (I_{qref_M} - I_{q_M}) \\ &\quad - \omega_M L_{d_M} I_{d_M} + \psi \omega_M \\ X_2 &= \frac{K_{ild_M}}{S} (I_{dref_M} - I_{d_M}) \\ X_3 &= \frac{K_{ilq_M}}{S} (I_{qref_M} - I_{q_M}) \end{aligned} \right. \quad (4)$$

The GSC implements grid voltage-oriented vector control to maintain the constant DC bus voltage and to manage the output of grid-connected reactive power. The dynamic equation as shown in Eq.(5).

$$\left\{ \begin{aligned} I_{dref_G} &= \left(K_{pQ_G} + \frac{K_{iQ_G}}{s} \right) (Q_{ref_G} - Q_G) \\ I_{qref_G} &= \left(K_{pVdc_G} + \frac{K_{iVdc_G}}{s} \right) (V_{dref_G} - V_{dc_G}) \\ X_4 &= \frac{K_{iQ_G}}{s} (Q_{ref_G} - Q_G) \\ X_5 &= \frac{K_{iVdc_G}}{s} (V_{dref_G} - V_{dc_G}) \end{aligned} \right. \quad (5)$$

(6): The GSC inner loop control dynamic equation as in Eq.

$$\left\{ \begin{aligned} V_{dref_G} &= - \left(K_{pld_G} + \frac{K_{ild_G}}{S} \right) \left(I_{dref_G} - I_{d_G} \right) \\ &\quad - \omega_G L_G I_{q_G} + V_{d_G} \\ V_{qref_G} &= - \left(K_{plq_G} + \frac{K_{ilq_G}}{S} \right) \left(I_{qref_G} - I_{q_G} \right) \\ &\quad + \omega_G L_G I_{d_G} + V_{q_G} \\ X_6 &= \frac{K_{ild_G}}{S} \left(I_{dref_G} - I_{d_G} \right) \\ X_7 &= \frac{K_{ilq_G}}{S} \left(I_{qref_G} - I_{q_G} \right) \end{aligned} \right. \quad (6)$$

The intermediate capacitor, positioned between the MSC and the GSC, plays a crucial role in voltage stabilization,

current filtration, energy storage, and overall system stability enhancement. Its dynamical equation is as shown in Eq. (7).

$$\frac{dV_{dc_G}}{dt} = \frac{I}{C_{MG}V_{dc_G}}(P_M + P_G) \quad (7)$$

The MSC and GSC power equations are as shown in Eq. (8) and Eq. (9).

$$\begin{cases} P_M = V_{d_M} I_{d_M} + V_{q_M} I_{q_M} \\ Q_M = V_{q_M} I_{d_M} - V_{d_M} I_{q_M} \end{cases} \quad (8)$$

$$\begin{cases} P_G = V_{d_G} I_{d_G} + V_{q_G} I_{q_G} \\ Q_G = V_{q_G} I_{d_G} - V_{d_G} I_{q_G} \end{cases} \quad (9)$$

2.2. MMC Model

In this section, variables shared between WFMMC and GSMMC are denoted with the subscript MMC. The parts specific to WFMMC are denoted with the subscript WF, while those specific to GSMMC are marked with the subscript GS.

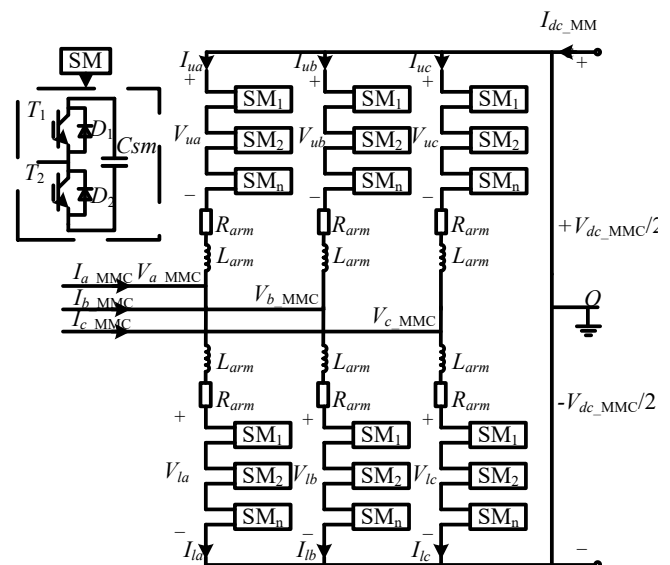


Fig.2. MMC Topology

The MMC topology is shown in Fig. 2, highlighting submodule. Its capacitance voltage includes DC component, AC base frequency component, AC double frequency negative order component and AC triple frequency component, as delineated in Eq.(10).

$$C_{sm} \frac{dV_{csm}}{dt} = C_{sm} \frac{d(V_{csm0} + V_{csm1} + V_{csm2} + V_{csm3})}{dt} \quad (10)$$

The dynamic characteristics of the DC voltage component of the submodule are as shown in Eq.(11).

$$\frac{dV_{csm0}}{dt} = \frac{1}{6C_{sm}} I_{dc_MMC} + \frac{V_{q_MMC} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} + \frac{V_{d_MMC} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} + \frac{V_{cirq} I_{cirq}}{2C_{sm} V_{dc_MMC}} + \frac{V_{cird} I_{cird}}{2C_{sm} V_{dc_MMC}} \quad (11)$$

The dynamic characteristics of the fundamental frequency component of the submodule voltage are as shown in Eq.(12).

$$\left\{ \begin{aligned} \frac{dV_{csm1d}}{dt} &= -\omega_{MMC} V_{csm1q} - \frac{1}{4C_{sm}} I_{d_MMC} - \frac{I_{dc_MMC} V_{d_MMC}}{3C_{sm} V_{dc_MMC}} \\ &\quad - \frac{V_{q_MMC} I_{cirq}}{2C_{sm} V_{dc_MMC}} - \frac{V_{d_MMC} I_{cird}}{2C_{sm} V_{dc_MMC}} \\ &\quad - \frac{V_{cirq} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} - \frac{V_{cird} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} \\ \frac{dV_{csm1q}}{dt} &= \omega_{MMC} V_{csm1d} - \frac{1}{4C_{sm}} I_{q_MMC} - \frac{I_{dc_MMC} V_{q_MMC}}{3C_{sm} V_{dc_MMC}} \\ &\quad - \frac{V_{d_MMC} I_{cirq}}{2C_{sm} V_{dc_MMC}} + \frac{V_{q_MMC} I_{cird}}{2C_{sm} V_{dc_MMC}} \\ &\quad - \frac{V_{cirq} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} + \frac{V_{cird} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} \end{aligned} \right. \quad (12)$$

The dynamic characteristics of the double-frequency component of the submodule voltage are as shown in Eq. (13).

$$\left\{ \begin{aligned} \frac{dV_{csm2d}}{dt} &= -2\omega_{MMC} V_{csm2q} - \frac{1}{2C_{sm}} I_{cird} - \frac{I_{dc_MMC} V_{cird}}{3C_{sm} V_{dc_MMC}} \\ &\quad - \frac{V_{q_MMC} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} + \frac{V_{d_MMC} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} \\ \frac{dV_{csm2q}}{dt} &= 2\omega_{MMC} V_{csm1d} + \frac{1}{2C_{sm}} I_{cirq} + \frac{I_{dc_MMC} V_{cirq}}{3C_{sm} V_{dc_MMC}} \\ &\quad + \frac{V_{d_MMC} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} + \frac{V_{q_MMC} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} \end{aligned} \right. \quad (13)$$

The dynamic characteristics of the triple-frequency component of the submodule voltage are as shown in Eq. (14).

$$\left\{ \begin{aligned} \frac{dV_{csm3x}}{dt} &= 3\omega_{MMC} V_{csm3y} - \frac{I_{cirq} V_{d_MMC}}{2C_{sm} V_{dc_MMC}} I_{cird} - \frac{I_{cird} V_{q_MMC}}{2C_{sm} V_{dc_MMC}} \\ &\quad - \frac{V_{cird} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} - \frac{V_{cirq} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} \\ \frac{dV_{csm3y}}{dt} &= -3\omega_{MMC} V_{csm3x} + \frac{I_{cirq} V_{q_MMC}}{2C_{sm} V_{dc_MMC}} I_{cird} - \frac{I_{cird} V_{d_MMC}}{2C_{sm} V_{dc_MMC}} \\ &\quad + \frac{V_{cirq} I_{q_MMC}}{4C_{sm} V_{dc_MMC}} - \frac{V_{cird} I_{d_MMC}}{4C_{sm} V_{dc_MMC}} \end{aligned} \right. \quad (14)$$

The dynamic characteristics of the DC current in MMC are shown in Eq.(15).

$$\frac{dI_{dc_MMC}}{dt} = \frac{3V_{dc_MMC}}{2L_{arm}} - \frac{3NV_{csm}}{L_{arm}} + \frac{3NV_{q_MMC} V_{csm1q}}{2L_{arm} V_{dc_MMC}} + \frac{3NV_{d_MMC} V_{csm1d}}{2L_{arm} V_{dc_MMC}} - \frac{3NV_{q_MMC} V_{csm2q}}{2L_{arm} V_{dc_MMC}} - \frac{3NV_{d_MMC} V_{csm2d}}{2L_{arm} V_{dc_MMC}} \quad (15)$$

The dynamic characteristics of the fundamental frequency component of the MMC current are as shown in Eq. (16).

$$\left\{ \begin{aligned} \frac{dI_{d_MMC}}{dt} &= \frac{R_{eq}}{L_{eq}} I_{d_MMC} + \frac{V_{sd_MMC}}{L_{eq}} + \frac{NV_{csm1d}}{2L_{eq}} \\ &\quad + N \frac{-2V_{csm} V_{d_MMC} - V_{csm2q} V_{q_MMC} - V_{csm2d} V_{d_MMC}}{2V_{dc_MMC} L_{eq}} \\ &\quad + N \frac{V_{cirq} V_{csm1q} + V_{cird} V_{csm1d}}{2V_{dc_MMC} L_{eq}} - \omega_{MMC} I_{q_MMC} \\ \frac{dI_{q_MMC}}{dt} &= -\frac{R_{eq}}{L_{eq}} I_{q_MMC} + \frac{V_{sq_MMC}}{L_{eq}} + \frac{NV_{csm1q}}{2L_{eq}} \\ &\quad + N \frac{-2V_{csm} V_{q_MMC} - V_{csm2q} V_{q_MMC} + V_{csm2d} V_{q_MMC}}{2V_{dc_MMC} L_{eq}} \\ &\quad + N \frac{V_{cirq} V_{csm1d} + V_{cird} V_{csm1q}}{2V_{dc_MMC} L_{eq}} + \omega_{MMC} I_{d_MMC} \end{aligned} \right. \quad (16)$$

The dynamic characteristics of the double-frequency circulating current of the MMC are as shown in Eq. (17).

$$\left\{ \begin{aligned} \frac{dI_{cird}}{dt} &= -2\omega_{MMC} I_{cirq} - \frac{NV_{csm2d}}{2L_{arm}} - \frac{NV_{csm} V_{cird}}{L_{arm} V_{dc_MMC}} \\ &\quad + N \frac{V_{d_MMC} V_{csm1d} - V_{q_MMC} V_{csm1q}}{2L_{arm} V_{dc_MMC}} \\ \frac{dI_{cirq}}{dt} &= 2\omega_{MMC} I_{cird} - \frac{NV_{csm2q}}{2L_{arm}} - \frac{NV_{csm} V_{cirq}}{L_{arm} V_{dc_MMC}} \\ &\quad + N \frac{V_{d_MMC} V_{csm1q} - V_{q_MMC} V_{csm1d}}{2L_{arm} V_{dc_MMC}} \end{aligned} \right. \quad (17)$$

The wind farm operates akin to a passive network connected to MMC-HVDC. The primary function of WFMMC is to stabilize an AC voltage at a consistent amplitude and frequency, necessitating island control. The control equations for its outer and inner loops can be expressed as follows, respectively shown in Eq. (18) and Eq. (19).

$$\begin{cases} I_{dref_WF} = \left(K_{pVd_WF} + \frac{K_{iVd_WF}}{s} \right) (V_{sdref_WF} - V_{sdm_WF}) \\ I_{qref_WF} = \left(K_{pVq_WF} + \frac{K_{iVq_WF}}{s} \right) (V_{sqref_WF} - V_{sqm_WF}) \\ X_8 = \frac{K_{iVd_WF}}{s} (V_{sdref_WF} - V_{sdm_WF}) \\ X_9 = \frac{K_{iVq_WF}}{s} (V_{sqref_WF} - V_{sqm_WF}) \end{cases} \quad (18)$$

$$\begin{cases} V_{cdref_WF} = - \left(K_{pld_WF} + \frac{K_{ild_WF}}{s} \right) (I_{dref_WF} - I_{dm_WF}) \\ \quad - \omega_{WF} L_{WF} I_{q_WF} + V_{sd_WF} \\ V_{cqref_WF} = - \left(K_{plq_WF} + \frac{K_{ilq_WF}}{s} \right) (I_{qref_WF} - I_{qm_WF}) \\ \quad + \omega_{WF} L_{WF} I_{d_WF} + V_{sq_WF} \\ X_{10} = \frac{K_{ild_WF}}{s} (I_{dref_WF} - I_{dm_WF}) \\ X_{11} = \frac{K_{ilq_WF}}{s} (I_{qref_WF} - I_{qm_WF}) \end{cases} \quad (19)$$

The task of GSMMC is to deliver designated reactive power to support the shore power grid while maintaining the constant DC side voltage of the system. Its outer and inner control equations are shown in Eq. (20) and Eq. (21).

$$\begin{cases} I_{dref_GS} = \left(K_{pVdc_GS} + \frac{K_{iVdc_GS}}{s} \right) (V_{dref_GS} - V_{dm_GS}) \\ I_{qref_GS} = \left(K_{pQ_GS} + \frac{K_{iQ_GS}}{s} \right) (Q_{ref_GS} - Q_{GS}) \\ X_{15} = \frac{K_{iVdc_GS}}{s} (V_{dref_GS} - V_{dm_GS}) \\ X_{16} = \frac{K_{iQ_GS}}{s} (Q_{ref_GS} - Q_{GS}) \end{cases} \quad (20)$$

$$\begin{cases} V_{dref_GS} = - \left(K_{pld_GS} + \frac{K_{ild_GS}}{s} \right) (I_{dref_GS} - I_{dm_GS}) \\ \quad - \omega_{GS} L_{GS} I_{q_GS} + V_{sd_GS} \\ V_{qref_GS} = - \left(K_{plq_GS} + \frac{K_{ilq_GS}}{s} \right) (I_{qref_GS} - I_{qm_GS}) \\ \quad + \omega_{GS} L_{GS} I_{d_GS} + V_{sq_GS} \\ X_{17} = \frac{K_{ild_GS}}{s} (I_{dref_GS} - I_{dm_GS}) \\ X_{18} = \frac{K_{ilq_GS}}{s} (I_{qref_GS} - I_{qm_GS}) \end{cases} \quad (21)$$

The circulating current, while not directly affect the AC and DC currents of the MMC, exerts an influence on the bridge arm currents. This results in an escalated the rated

current of the sub-module, subsequently impacting the performance of the converter. To mitigate these effects, a control strategy for suppressing MMC circulating currents has been formulated, as depicted in Eq. (22).

$$\begin{cases} V_{cird} = \left(K_{pcir_MMC} + \frac{K_{icir_MMC}}{s} \right) (I_{cirdref} - I_{cird}) \\ \quad + 2\omega_{MMC} L_{arm} I_{cirq} \\ V_{cirq} = \left(K_{pcir_MMC} + \frac{K_{icir_MMC}}{s} \right) (I_{cirqref} - I_{cirq}) \\ \quad + 2\omega_{MMC} L_{arm} I_{cird} \end{cases} \quad (22)$$

The MMC AC bus interface and the voltage are as follows:

$$\begin{cases} V_{sd_MMC} = U_m \sin(\theta_0 - \theta_{MMC}) - R_{eq} I_{d_MMC} \\ \quad - L_{eq} \frac{dI_{d_MMC}}{dt} - \omega_{MMC} L_{eq} I_{q_MMC} \\ V_{sq_MMC} = U_m \cos(\theta_0 - \theta_{MMC}) - R_{eq} I_{q_MMC} \\ \quad - L_{eq} \frac{dI_{q_MMC}}{dt} + \omega_{MMC} L_{eq} I_{d_MMC} \end{cases} \quad (23)$$

2.3. Phase-Locked Loop Model

The transformation of three-phase line voltage into dq components allows the q-axis component to be modulated by a PI controller, yielding an output frequency. This output frequency is integrated to generate a phase-locked loop angle. Through feedback control, the output frequency matches the input frequency, achieving phase locking with a fixed phase difference. The dynamic equation is:

$$\begin{cases} \omega_{MMC} = \omega_0 + \left(k_{pPLL} + \frac{k_{iPLL}}{s} \right) V_{sq_MMC} \\ \theta_{MMC} = \frac{\omega_0}{s} \end{cases} \quad (24)$$

2.4. Establishment of Small Signal Model

Small signal model is an important theoretical basis for power system stability analysis and parameter optimization design. Upon minimal disturbances, a nonlinear complex system exhibits only slight variances, permitting linearization of the system. Through this analytical method, complex differential equations can be transformed into solving the stability of the equilibrium state of the system.

The mathematical model of MMC-HVDC grid connection system for offshore wind farm can be expressed as:

$$\frac{dx}{dt} = y(x) \quad (25)$$

The state variable of the system at the steady-state working point is x_0 , and satisfies:

$$\frac{dx_0}{dt} = y(x_0) = 0 \quad (26)$$

When the system receives a small interference, the state variable will make small changes at the steady-state working point, namely:

$$x = x_0 + \Delta x \quad (27)$$

this moment:

$$\frac{dx}{dt} = y(x_0 + \Delta x) \quad (28)$$

Following this methodology, the MMC and PMSG variables are referred to the same rotating coordinate system, culminating in the establishment of a small-signal model for the MMC-HVDC. The state variables and their numbering of the small-signal model are shown in Table 1.

Utilizing the PSCAD electromagnetic transient simulation software, a modification in the GSMC DC voltage setpoint from 800 kV to 774 kV, the dynamic responses of the small-signal model and the electromagnetic transient model can be seen to be consistent in Fig 3. This proves the correctness of the small-signal model.

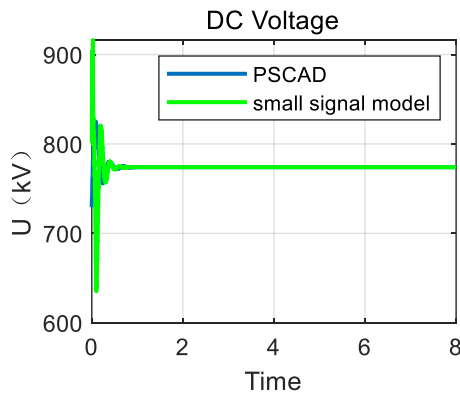


Fig.3. PSCAD DC Voltage Simulation

Table 1. Small Signal Model State Variables

1	ΔV_G	24	ΔV_{csm1d_WF}	47	ΔV_{csm1d_GS}
2	ΔI_{d_M}	25	ΔV_{csm1q_WF}	48	ΔV_{csm1q_GS}
3	ΔI_{q_M}	26	ΔV_{csm2d_WF}	49	ΔV_{csm2d_GS}
4	$\Delta \omega_M$	27	ΔV_{csm2q_WF}	50	ΔV_{csm2q_GS}
5	ΔX_1	28	ΔV_{csm3x_WF}	51	ΔV_{csm3x_GS}
6	ΔX_2	29	ΔV_{csm3y_WF}	52	ΔV_{csm3y_GS}

7	ΔX_3	30	ΔI_{d_WF}	53	ΔI_{d_GS}
8	ΔV_{dc_G}	31	ΔI_{q_WF}	54	ΔI_{q_GS}
9	ΔI_{d_G}	32	ΔI_{cird_WF}	55	ΔI_{cird_GS}
10	ΔI_{q_G}	33	ΔI_{cirq_WF}	56	ΔI_{cirq_GS}
11	ΔX_4	34	ΔX_{13}	57	ΔX_{20}
12	ΔX_5	35	ΔX_{14}	58	ΔX_{21}
13	ΔX_6	36	ΔI_{dm_WF}	59	ΔI_{dm_GS}
14	ΔX_7	37	ΔI_{qm_WF}	60	ΔI_{qm_GS}
15	ΔV_{sdm_WF}	38	ΔV_{sdm_GS}	61	ΔV_{dcm_GS}
16	ΔV_{sqm_WF}	39	ΔV_{sqm_GS}	62	ΔI_{dc_DCL1}
17	ΔX_8	40	ΔX_{15}	63	ΔI_{dc_DCL2}
18	ΔX_9	41	ΔX_{16}	64	ΔI_{dc_DCL3}
19	ΔX_{10}	42	ΔX_{17}	65	ΔI_{dc_WF}
20	ΔX_{11}	43	ΔX_{18}	66	ΔV_{dc_WF}
21	ΔX_{12}	44	ΔX_{19}	67	ΔI_{dc_GS}
22	$\Delta \theta_{PM}$	45	$\Delta \theta_{AC}$	68	ΔV_{dc_GS}
23	ΔV_{csm0_WF}	46	ΔV_{csm0_GS}		

3. Oscillation Inhibition Strategy

3.1. Selection of the Dominant Controller

Drawing on the small signal interference model established in Section 2.4, we extract the state matrix A and obtain the feature root of the small interference state space model. The feature root, manifesting either real numbers or complex numbers. In classical control theory, if all the real parts of the feature root are considered gradually stable, as long as there is a non-negative real root in the feature root, the system is considered unstable, that is, the oscillation is divergent. For the N-order matrix, exactly N eigenvalues are identified. If the state matrix is real, then the complex eigenvalues invariably occur in conjugate pairs, each pair corresponding to a specific oscillatory mode. For any pair of system eigenvalues, there are:

$$\lambda_{i,i+1} = \alpha_i \pm j\beta_i \quad (29)$$

The real part determines the degree of damping of the corresponding oscillation mode, while the imaginary part indicates the frequency.

The corresponding oscillation frequency can be calculated, and the calculated formula is:

$$f_i = \frac{\beta_i}{2\pi} \quad (30)$$

The damping ratio is the ratio of the real part to the magnitude of the characteristic roots, and it is used to calculate the decay characteristics of the oscillatory response.

$$\xi_i = -\frac{\alpha_i}{\sqrt{\alpha_i^2 + \beta_i^2}} \quad (31)$$

The characteristics of the system oscillation mode are mainly dependent on the damping ratio. A positive damping ratio yields a stable oscillation pattern, with an increase in the ratio correlating with an accelerated decay in oscillation amplitude. When the damping ratio is less than zero, the corresponding oscillation mode is unstable. At a zero damping ratio, the oscillatory achieves a condition termed as boundary stable. The oscillation modes in the system are displayed in Table 2.

Table 2. System Oscillation Mode

Oscillation Mode	Characteristic Roots	Frequency	Damping Ratio
1	$-4695.58 \pm 358.94i$	57.126	0.997
2	$-2547.04 \pm 205.73i$	32.743	0.997
3	$-526.34 \pm 4095.53i$	651.823	0.127
4	$-5.52 \pm 1062.78i$	169.147	0.005
5	$-11.59 \pm 956.96i$	152.305	0.012
6	$-7.52 \pm 956.96i$	152.300	0.008
7	$-51.23 \pm 723.39i$	115.131	0.071
8	$-61.08 \pm 710.57i$	113.091	0.086
9	$-29.80 \pm 444.86i$	70.801	0.067
10	$-43.69 \pm 502.80i$	80.023	0.087
11	$-236.24 \pm 439.35i$	69.924	0.474
12	$-30.60 \pm 351.13i$	55.884	0.087
13	$-254.20 \pm 297.15i$	47.293	0.650
14	$-262.44 \pm 187.71i$	29.875	0.813

15	$-81.59 \pm 232.96i$	37.077	0.331
16	$-278.19 \pm 184.96i$	29.438	0.833
17	$-52.85 \pm 268.04i$	42.660	0.193
18	$-98.86 \pm 101.04i$	16.080	0.699
19	$-94.19 \pm 104.62i$	16.651	0.669
20	$-10.93 \pm 74.18i$	11.805	0.146
21	$-4.75 \pm 20.93i$	3.331	0.221

The right eigenvector of the state-space matrix is indicative of the observability of a state variable with respect to the corresponding oscillation mode, while the left eigenvector indicates the controllability of a state variable to the corresponding oscillation mode. The calculation of the participation factor can visually reflect the degree of correlation between state variables and oscillation modes. The calculation formula is as follows:

$$p_{ki} = \phi_{ki} \psi_{ki} \quad (32)$$

In Eq. (32), ϕ_{ki} and ψ_{ki} represent the elements of the k -th row and i -th column of the left and right eigenvectors, respectively. The participation factor p_{ki} is an element of the participation matrix, indicating the degree of involvement of the k -th state variable in the i -th oscillation mode.

As depicted in Fig.4, the influence factors of most oscillatory modes are distributed in PMSG, WFMMC, GSMMC, and DCL. Oscillatory mode 1 is mainly caused by GSMMC. Oscillatory modes 2,5,6,7,8, and both WFMMC and GSMMC are involved. The oscillation dynamics of the system are the result of the joint action of all parts of the flexible direct transmission system. Therefore, it is necessary to suppress and optimize the whole system comprehensively.

Twelve dominant controllers are selected as variables for optimization based on participation factors, as shown in Table 3.

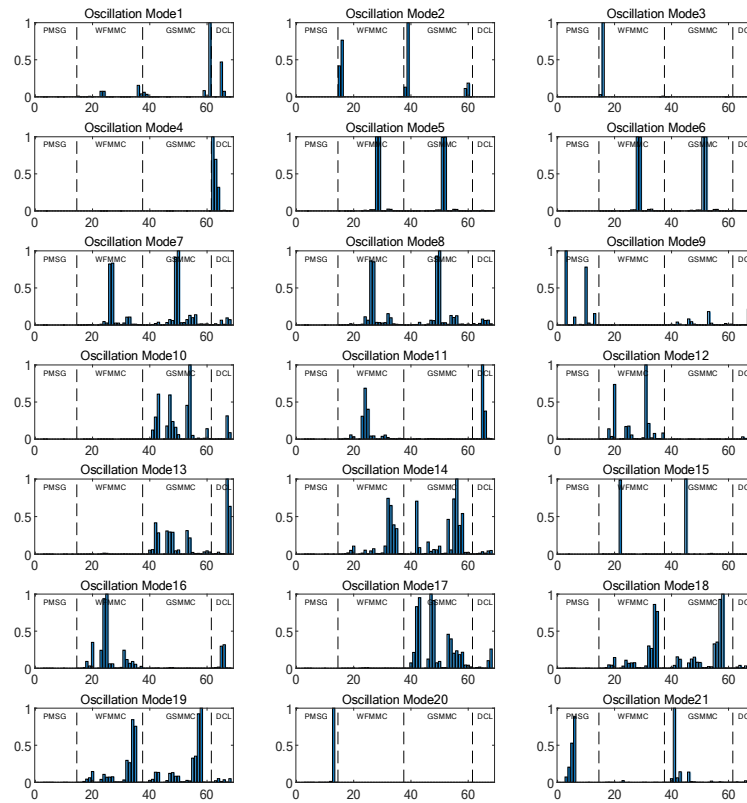


Fig.4. System Oscillation Participation Factors

Table 3. System Oscillation Dominates the Controller

number	Subsystem	parameter
1	PMSG	$K_{p\omega_M}, K_{i\omega_M}$
2		K_{plq_M}, K_{ilq_M}
3		K_{pQ_G}, K_{iQ_G}
4		K_{pld_G}, K_{ild_G}
5	WFMMC	K_{pVd_WF}, K_{iVd_WF}
6		K_{pVq_WF}, K_{iVq_WF}
7		K_{pld_WF}, K_{ild_WF}
8		K_{plq_WF}, K_{ilq_WF}
9		K_{pcir_WF}, K_{icir_WF}
10	GSMMC	K_{pVdc_GS}, K_{iVdc_GS}
11		K_{pQ_GS}, K_{iQ_GS}
12		K_{plq_GS}, K_{ilq_GS}

3.2. Construction of objective functions

In the stable case, the primary considerations include oscillation mode and the negative real characteristic root. The optimization indices selected are the damping ratio associated with the oscillation mode and the distance from the negative real number root to the virtual axis. The feature root optimization region is shown in Fig. Due to interdependence among controllers across various systems, positive characteristic roots may precipitate instability in the

parameter optimization process, so this phenomenon is prevented by increasing the penalty function. The objective function is:

$$L = \sum_{j=1}^{np} \sum_{\alpha_{ij} > \alpha_0} (\alpha_{ij} - \alpha_0)^2 + a \sum_{j=1}^{np} \sum_{\xi_{ij} \leq \xi_0} (\xi_{ij} - \xi_0)^2 + \sum_{k=1}^{n-2np} \sum_{\alpha_{ij} > 0} b \quad (33)$$

Where L represents the optimization objective function of the algorithm; np represents the number of oscillatory modes of the system; α_{ij} represents the real part of the complex characteristic roots; α_0 represents the optimization objective of the real part of the oscillatory mode characteristic roots; a represents the damping ratio adjustment factor; ξ_{ij} represents the damping ratio of the oscillatory modes; ξ_0 represents the target value of the damping ratio optimization; n represents the order of the matrix; $n - 2np$ represents the number of real roots; b represents the penalty function factor.

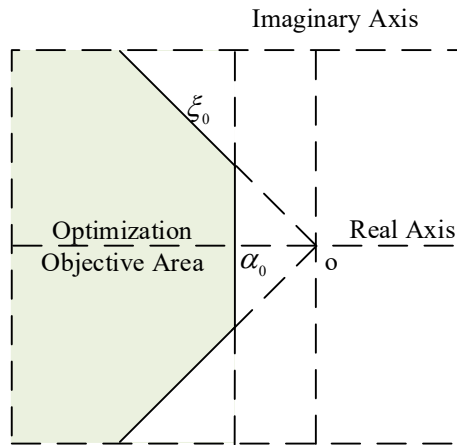


Fig.5. Algorithm Optimization Target Area

3.3. Optimization Algorithm

3.3.1 Comparison of Several Meta-heuristic Algorithms

Historically, a plethora of heuristic optimization algorithms has been evaluated and adopted in the design of damped controllers. In this regard, the domain of power systems has seen a growing affinity for the adoption of heuristic techniques in the design of damped power controllers. The technique utilizes a stochastic approach to ascertain the best solution, guided by a defined objective function. Each algorithm is distinguished by its inherent advantages and limitations. The GWO performs excels in both exploration and development by simulating the social hierarchy and hunting behavior of the gray wolves. It is suitable at navigating complex optimization problems, although its efficacy diminishes in high-dimensional problems. The SSA is inspired by the sparrow foraging and anti-predation strategies, highlighting communal information dissemination, which facilitates rapid convergence to the global optimum, but its stability and convergence rates are significantly influenced by the initial parameter setting. The WOA, emulating the humpback whale's hunting techniques, especially its spiral updating mechanism, is adept at addressing nonlinear problems, but may fall into local optima on the multi-peak problem. NGO [34] inspired by goshawk hunting strategies, is proficient in extensive space searches, but is computationally intensive and thus demands substantial computing resources. The DBO simulates the tumbling behavior of the mantis, making it particularly effective for multi-target optimization problems, though it may falter in highly intricate single-target problems. The selection and fine-tuning of each algorithm must be tailored to the specific application scenarios and requirements.

3.3.2 DBO Algorithm Improvement Strategy

In the basic DBO, the population initialization adopts random distribution, which reduces the diversity of the algorithm and reduces the individual optimization algorithm. This approach also skews the balance between global exploration and local development ability, often leading to sub-optimal local optimal and impaired global exploration

ability. The following four strategies are introduced to address the above shortcomings:

Chaos mapping integrates deterministic and stochastic method in nonlinear dynamical systems. In the initialization position update process, the chaotic variable replaces the random variables in the intelligent algorithm process, thereby expanding the solution space search range beyond that of probability-based random search strategy. Therefore, for the random initialization process, chaotic initialization enhances both the population diversity and the convergence rate of the optimization algorithm. Here, the segmented linear chaotic mapping is employed, described by the following equation [35]:

$$X_{t+1} = \begin{cases} \frac{X_t}{P} & 0 \leq X_t < P \\ \frac{X_t - P}{0.5 - P} & P \leq X_t < 0.5 \\ \frac{1 - P - X_t}{0.5 - P} & 0.5 \leq X_t < 1 - P \\ \frac{1 - X_t}{P} & 1 - P \leq X_t \leq 1 \end{cases} \quad (34)$$

Where, P is the control parameter for this map, $P \in [0,1]$, $P = 0.35$ in this paper.

Dung beetles breeding stage position update formula Eq.(35).

$$X_{t+1} = X^b + b_1 (X_t - Lb^*) + b_2 (X_t - Ub^*) \quad (35)$$

After applying the spiral search strategy, the position update formula is shown as Eq.(37).

$$z = e^{\cos\left(\frac{\pi t}{\text{Max_iteration}}\right)} \quad (36)$$

$$X_{t+1} = X^b + e^{z l} \cos(2\pi l) \cdot b_1 (X_t - Lb^*) + e^{z l} \cos(2\pi l) \cdot b_2 (X_t - Ub^*) \quad (37)$$

Where z determines the shape of the spiral.

Levy flight is a search strategy that enables long-step exploration to efficiently explore a wide range of search space, while exploiting shorter steps for local search. The expression for Levy flight is as follows[32]:

$$\text{Levy}(\lambda) \sim \frac{\left[\frac{\Gamma(1+\lambda) \sin(\pi\lambda/2)}{\Gamma(1+\lambda/2) \lambda 2^{(\lambda-1)/2}} \right]^{1/\lambda} u}{|v|^{1/2}} \quad (38)$$

Where: u , v , follow a normal distribution.

In the standard DBO algorithm, the position update formula during the dung beetle's stealing phase is as follows:

$$X_{t+1} = X^b + S \cdot g \cdot (|X_t - X^*| + |X_t - X^b|) \quad (39)$$

Where S is a constant, and g is a random variable following a normal distribution. After incorporating the Levy flight enhancement, the equation can be represented as:

$$X_{t+1} = \text{Levy}(X^b) + S \cdot g \cdot (|X_t - X^*| + |X_t - X^b|) \quad (40)$$

To fully increase the diversity of the mantis population, the t-distribution was introduced to vary the optimal individual, expand the search range, and determine the variation by comparing the fitness before and after the variation. As shown in Eq.(41).

$$X_{t+1} = X_t + X_t \cdot t(\text{teration}) \quad (41)$$

Where t represents the function of the t-distribution, and teration is the degree of freedom of the t-distribution, which corresponds to the number of iterations.

4. Simulation and Results

4.1. Validation of Algorithm Effectiveness

To validate the optimal performance of the algorithm, this paper selects 6 test functions from a set of 23 established benchmark test functions for simulation experiments, as shown in Table 4. Among them, unimodal functions F1 and F2 assess the convergence the speed and accuracy; multimodal functions F3-F4, composite functions F5-F6, featuring a singular global optimum and multiple local optima, appraise the algorithm's capability for global search and mining capability of the algorithm. The functions' characteristics—the name, dimension, value range and theoretical optimum—are enumerated in the table. The experimental environment is Windows 11 operating system, the CPU is Intel (R) Core (TM) i7-9750H, the memory is 16GB, and the integrated development environment is Matlab2022a.

Table 4. Algorithm Test Function

Function		Dim	Range	Theoretical optimal value
F1	sphere	30	[-100,100]	0
F2	schwefel 2.22	30	[-10,10]	0
F3	Schwefel 2.26	30	[-500,500]	-12569.5
F4	Rastrigin	30	[-5.12,5.12]	0
F5	Shekel's Foxholes	2	[-65.536,65.536]	1
F6	Kowalik	4	[-5,5]	0.000308

To robustly ascertain the optimal performance and robustness of various intelligent algorithms and TDBO, a comparative analysis was conducted against GWO, SSA, WOA, NGO, and DBO. To mitigate stochastic variances,

each algorithm runs independently on F1-F6, the dimension of unimodal and multimodal function is 30, and the maximum number of iterations is 100. Algorithmic performance of meta-heuristic algorithms is determined by the difference between the final output results and the theoretical optimal values of benchmark functions; closer values indicate superior performance and vice versa. In 30 independent trials were conducted for each algorithm yields 30 results for each test functions, generating a dataset comprising the extreme values (both maximum and minimum). This dataset was utilized to derive the standard deviation, which serves as a measure of the algorithm in each independent solution. The algorithmic performance was then quantitatively assessed using four primary metrics: the best, worst, mean, and standard. The results are presented in Table 5, where the best values for each metric are highlighted in bold.

In F1 and F2, the TDBO algorithm exhibited superior performance all four metrics: worst value, optimal value, mean value and standard deviation. In F3, the best performance was achieved in the worst value, optimal value, mean value and standard deviation. In F4, the best results of GWO, SSA, WOA, DBO, TDBO converged to 0 for 30 independent runs except NGO. And the worst value of SSA and TDBO can also reach the optimal target value of the benchmark test function. In F5, the worst NGO from 30 independent were nearest to the benchmark's the target value. The optimal value of all six algorithms can converge to points close to the optimal target value of the function, with the NGO algorithm outperforming the others in terms of mean and standard deviation. In F6, the solution results of NGO algorithm on the worst value standard were closest to the optimal target value, but TDBO has the highest solution accuracy on the optimal value. In conclusion, the accuracy and stability of the TDBO algorithm achieved the best performance compared to its counterparts in solving the single-peak and multi-peak functions, although NGO algorithm exhibited marginally better than TDBO algorithm.

The temporal efficiency of each independent run and the results are shown in the Table 6. From F1-F6, the WOA consistently required the shortest computation time. Relative to DBO algorithm, TDBO computational time was 1.168 times longer in F5 and 2.12 times longer in F3, indicating that while TDBO's strategic enhancements improve the accuracy of the algorithm and the stability of the solution, they also necessitate a higher computing resources allocation.

To facilitate a more rigorous analysis of algorithmic convergence, this paper draws the convergence curves of several heuristic algorithms on six benchmark functions, with the horizontal axis representing iteration count and the vertical axis representing the fitness values, as illustrated in Fig.5. Analysis reveals that TDBO exhibits superior rapidity and precision in convergence, particularly for the F1-F2 in 100 iterations. In F1 and F2, TDBO can converge to near the optimal value at the speed of the approximate line. This underscores TDBO's exceptional accuracy and effectiveness in addressing the single peak function. In contrast, for the function F3, TDBO reached the optimal value after 40

iterations, whereas the WOA algorithm approximates the optimal value after 10 iterations, but succumbs to local optimum without escaping within 100 iterations. In F4, both TDBO and SSA converge to the optimal value, but TDBO converges to 0 after 44 iterations, significantly outpacing SSA, which requires 63 iterations. In F5, despite SSA closely approaching the optimal solution due to the high initial value quality, it, akin to WOA, fails to overcome local optimum. But TDBO, DBO and NGO demonstrate the capability to transcend local optimum and converge to the target values,

with NGO exhibiting the most robust convergence. In F6, while GWO, NGO, and WOA stagnate at the local optimum solution in the middle of the iteration, TDBO and DBO exhibit consistent capability to transcend local optima. In conclusion, TDBO emerges as the preeminent algorithm in solving for optimal values, characterized by its high solution accuracy and convergence ability. Moreover, DBO and TDBO display commendable search and exploration capacities in circumventing local optimization.

Table 5. Algorithm Test Results

Fuction	Algorithm	Worst Value	Best Value	Mean Value	Standard Deviation
F1	GWO	4.60e-02	2.55e-03	1.30e-02	9.71e-03
	SSA	6.14e-27	1.39e-194	2.23e-28	1.12e-27
	WOA	4.06e-10	3.21e-16	1.65e-11	7.38e-11
	NGO	2.72e-13	5.74e-15	3.83e-14	4.94e-14
	DBO	7.10e-15	1.14e-37	2.55e-16	1.30e-15
	TDBO	5.56e-156	0	1.85e-157	1.02e-156
F2	GWO	4.02e-02	1.46e-02	2.34e-02	6.17e-03
	SSA	9.95e-14	5.93e-152	4.94e-15	1.86e-14
	WOA	6.48e-08	2.86e-11	7.75e-09	1.54e-08
	NGO	1.21e-07	2.04e-08	5.21e-08	2.70e-08
	DBO	3.29e-08	1.08e-17	3.44e-09	9.28e-09
	TDBO	1.95e-153	2.18e-225	6.50e-155	3.56e-154
F3	GWO	-3.17e+03	-6.72e+03	-5.47e+03	9.16e+02
	SSA	-6.46e+03	-9.43e+03	-8.14e+03	7.08e+02
	WOA	-6.55e+03	-1.26e+04	-9.25e+03	1.64e+03
	NGO	-4.30e+03	-5.57e+03	-4.81e+03	3.33e+02
	DBO	-1.17e+04	-1.26e+04	-1.23e+04	2.99e+02
	TDBO	-1.24e+04	-1.26e+04	-1.25e+04	2.99e+01
F4	GWO	9.02e+01	1.80e+01	3.38e+01	1.36e+01
	SSA	0	0	0	0
	WOA	9.43e+01	0	3.41e+00	1.72e+01
	NGO	3.01e-06	1.71e-13	1.00e-07	5.50e-07
	DBO	2.11e-09	0	7.06e-11	3.85e-10
	TDBO	0	0	0	0
F5	GWO	1.83e+01	9.98e-01	6.31e+00	4.42e+00
	SSA	1.27e+01	9.98e-01	2.56e+00	3.87e+00
	WOA	1.08e+01	9.98e-01	4.40e+00	3.62e+00
	NGO	1.01e+00	9.98e-01	9.98e-01	1.75e-03
	DBO	1.08e+01	9.98e-01	2.19e+00	2.20e+00
	TDBO	1.27e+01	9.98e-01	4.18e+00	3.07e+00
F6	GWO	2.04e-02	3.17e-04	2.94e-03	6.05e-03
	SSA	7.83e-04	3.07e-04	3.87e-04	1.69e-04
	WOA	1.93e-02	3.30e-04	1.51e-03	3.40e-03
	NGO	6.98e-04	3.48e-04	4.99e-04	1.09e-04
	DBO	2.23e-03	3.09e-04	7.69e-04	4.06e-04
	TDBO	5.48e-03	3.22e-04	1.09e-03	1.06e-03

Table 6. Runtime of the Algorithm for 100 Iterations on the Test Function

	GWO	SSA	WOA	NGO	DBO	TDBO
F1	0.025388	0.022434	0.012197	0.015181	0.013441	0.024513
F2	0.028027	0.025176	0.012744	0.014237	0.014315	0.024432
F3	0.033630	0.028646	0.016216	0.019592	0.019364	0.041054

F4	0.028877	0.022918	0.013391	0.019724	0.015122	0.026128
F5	0.083046	0.137452	0.082939	0.137800	0.076299	0.089138
F6	0.020312	0.021736	0.014302	0.015058	0.016425	0.027173

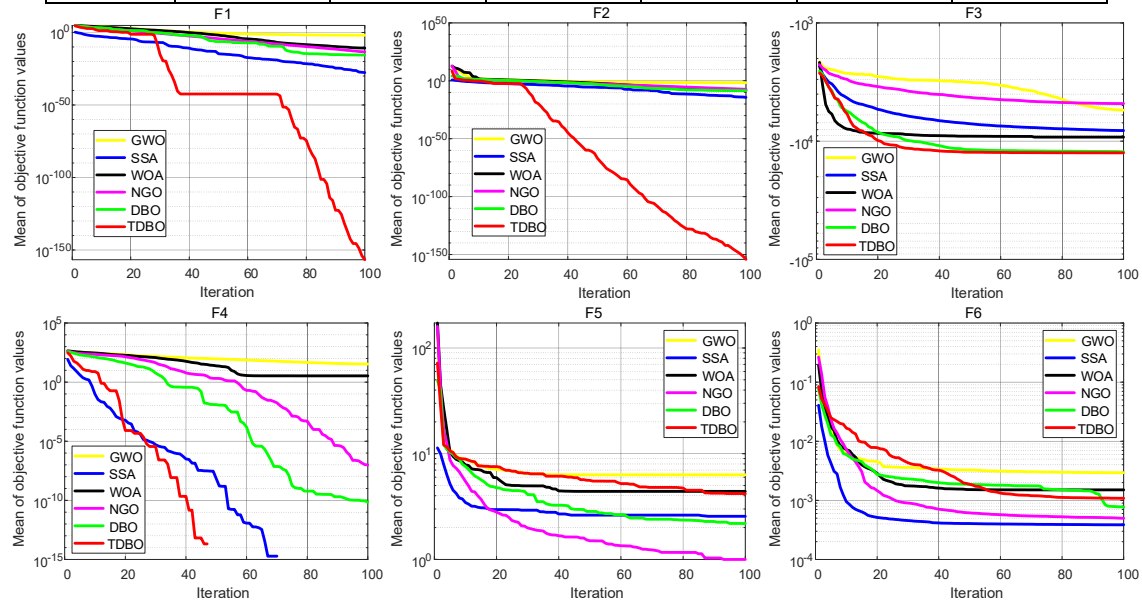


Fig.5. Optimization Algorithm Convergence Curve

4.2. Solution of the Oscillation Problem

4.2.1 Simulation of Steady-State Operation of MMC-HVDC

In the model established in Section 3, six heuristic algorithms were used for solving, with each algorithm executed 30 times independently, and the iteration limit set at 200. Evaluation indices included the worst value, optimal value, average value, and standard deviation, along with convergence accuracy and stability of the response algorithm. The convergence curves are displayed in Fig.6.

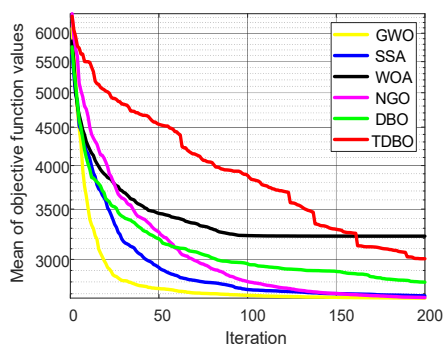


Fig.6. Steady-State MMC-HVDC Model Convergence Curve

The results of the 200 iterations, as depicted in Table 7, diverges from the findings in Section 4.1. Although TDBO demonstrated commendable performance on the benchmark test functions, it showed the slowest convergence speed. Conversely, WOA displayed rapid convergence in initial iterations but subsequently became ensnared in local optima. GWO, SSA, NGO, and DBO showed robust convergence

rates, with GWO consistently achieving the fastest convergence and providing stable results in multiple test runs. From the standard deviation, NGO showed the best solution stability, albeit at a computational time double that of GWO. Overall, among these algorithms, GWO emerged as the optimal algorithm for enhancing MMC-HVDC oscillation characteristics through the small-signal model optimization.

For the benchmark test functions, algorithm iterations were swift, taking less than 0.1 seconds for 100 iterations. However, solving this model necessitated at least 153 seconds for 200 iterations, attributed to the state space of the small-signal model represented by a 68×68 matrix. The stability issue of the small-signal model constitutes an eigenvalue optimization problem, requiring parametric adjustments within the matrix to align eigenvalues within the target area. Each iteration entails inserting parameters into the matrix to solve for its eigenvalues and calculating the oscillation frequency and damping ratio using the methods described in Section 3.1. The order of the matrix and the requisite computational steps amplify the complexity of the model.

After optimizing the controller parameters, the distribution of the model's eigenvalues before and after optimization was plotted in the complex coordinate system, as shown in Fig.7. The optimization target zone is demarcated by green dashed lines on the left side of the plot. Post-optimization, a notable clustering of eigenvalues was observed within the target area, especially those coordinates near the point (0,0) shifting towards the negative half-axis. From both the perspective of the objective function and the graph, it can be seen that a marked improvement in the system's overall damping ratio, suggesting an enhanced decay rate of oscillations in response to minor disturbances. All six

algorithms could demonstrate efficacy in ameliorating the oscillation characteristics of the MMC-HVDC. However, some eigenvalues continue to approach proximity to the imaginary axis. From the analysis of participation factors, this

is attributable to the system's structural parameters. Improvements may be achieved through modifications to the structural configuration and incorporating supplementary control strategies.

Table 7. Optimization Results of the MMC-HVDC Model

Algorithm	Worst Value	Best Value	Mean Value	Standard Deviation	Runtime
GWO	2821.15	2601.58	2664.38	40.60	153.93
SSA	3388.36	2610.53	2683.15	139.32	257.23
WOA	6423.55	2727.47	3221.60	690.34	153.75
NGO	2693.73	2650.49	2669.07	11.11	308.50
DBO	3231.49	2579.33	2798.00	168.97	154.54
TDBO	4631.12	2670.35	3006.02	1296.52	154.43

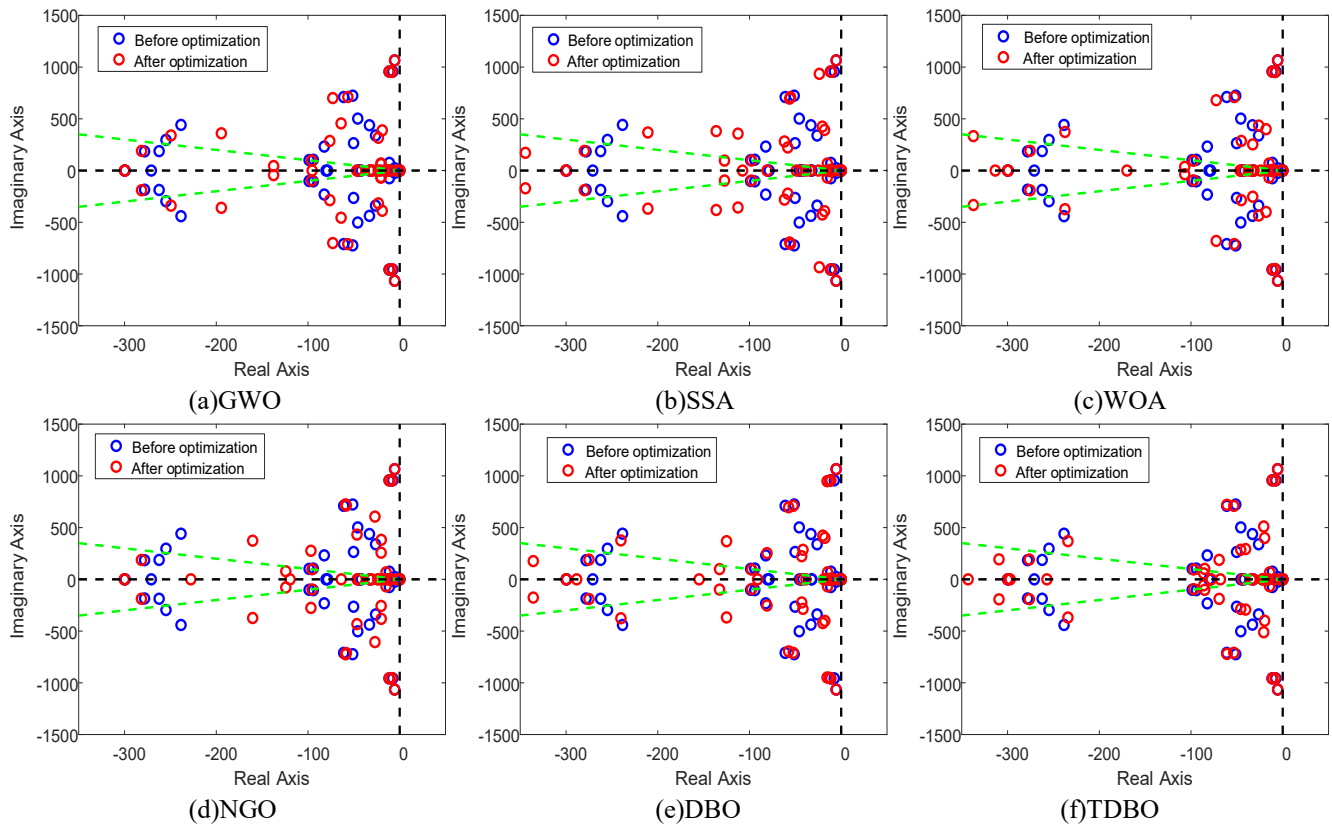


Fig.7. The Characteristic Roots of the MMC-HVDC System Before and After Optimization Under Steady-State Conditions

4.2.2 Simulation of Transient Instability in MMC-HVDC

To validate the robustness of the optimization strategy and to more emphatically validate the effectiveness of the optimization, system stability was intentionally compromised under unstable operating conditions.

The control chain delay of WFMMC significantly affects system stability[36]. By incrementally increasing the outer-loop delay parameter of the q-axis in the WFMMC controller

from $188 \mu s$ with a step size of $25 \mu s$ to $688 \mu s$, the trajectories of the characteristic roots are shown in Fig.8. As T_{IVq_WF} increases, multiple eigenvalues shift to the right, reducing the system's stability margin. Specifically, one oscillation mode transitioned beyond the right side of the imaginary axis, indicating the system entering an unstable state.

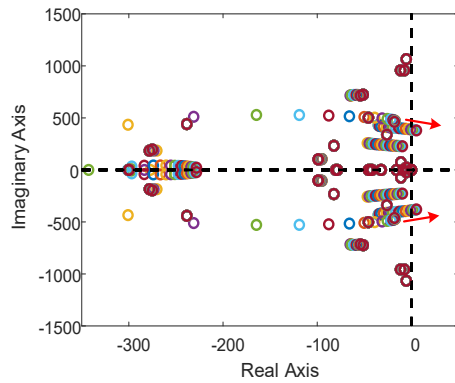


Fig.8. Trajectories of Characteristic Roots as T_{ivq_WF} Increases

We selected the GWO algorithm, which exhibited superior performance in steady-state conditions, alongside an enhanced PSO algorithm from reference [10] for model optimization under unstable conditions. The convergence curves are shown in Fig.9, where the GWO algorithm demonstrates rapid convergence. However, the method described in reference [10], frequently encounters local optima during iterations, thereby inhibiting further converge and ultimately unable to re-establish system stability.

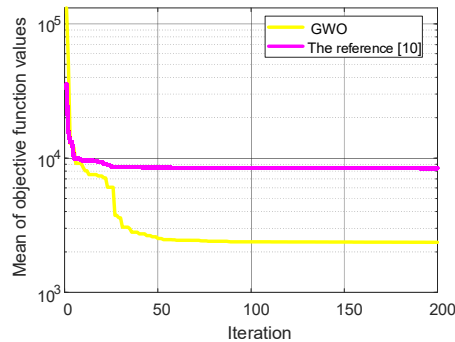
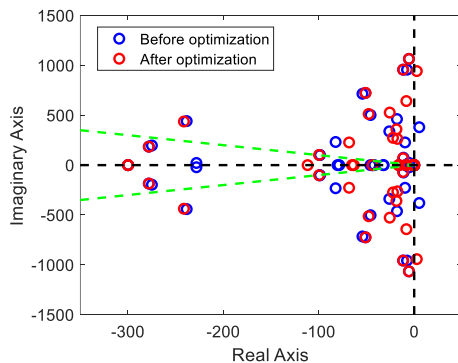
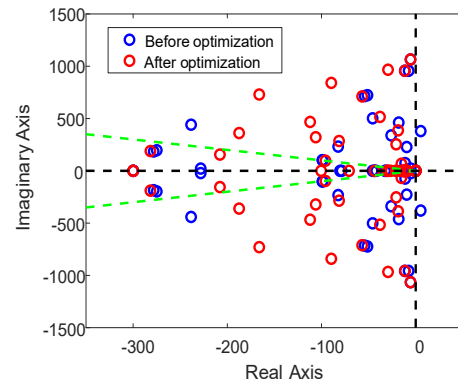


Fig.9. The MMC-HVDC Model Convergence Curve Under Unstable Conditions



(a)The Method Described in Reference [10].



(b)GWO

Fig.10. The Characteristic Roots of the MMC-HVDC System Before and After Optimization Under Unstable Conditions

Prior to the optimization of controller parameters, an increase in the delay parameter of the q-axis outer loop led to a displacement of one pair of characteristic roots into the right half-plane. Although the method from reference [10] moves this characteristic root into the left half-plane after optimization, it resulted in another pair of characteristic roots migrating to the right half-plane, indicating that the system remains in an unstable state, as shown in Fig.10(a). After optimizing the controller parameters using the GWO algorithm, all characteristic roots move to the left half-plane, thus restoring the system stability. This underscores the efficacy of the GWO algorithm in bolstering system stability, even under unstable conditions.

5. Conclusion

This paper delineates the formulation of a small-signal model for an offshore wind farm grid-connected through an MMC-HVDC system, incorporating the triple-frequency voltage component of the sub-modules. The dominant controller was selected for parameter optimization by employing the participation factor method. In terms of enhancing the controller optimization algorithm, the DBO algorithm was selected and refined. On the benchmark test functions, TDBO demonstrated excellent precision and stability. Techniques such as chaotic mapping, spiral search strategy, Levy flight, and t-distribution-based perturbation strategy have improved the resolution accuracy of the DBO algorithm and its proficiency in evading local optima. When addressing more complex small-signal models for flexible DC transmission, multiple algorithms including GWO, SSA, WOA, NGO, DBO, and TDBO all achieved the optimization goal, aligning the eigenvalues of the state matrix to the target area. However, GWO outperformed other algorithms on this model, further validating the "no free lunch" theorem. Considering computational precision and speed, GWO is deemed particularly apt for stability challenges associated with offshore wind farms grid-connected through an MMC-HVDC system based on eigenvalue optimization. In addition, GWO still demonstrates optimization effectiveness, even under system instability conditions.

This paper delineates the exploration of offshore direct-drive wind farms connected to the grid through MMC-HVDC systems, emphasizing modeling, oscillation mechanism analysis, and stability optimization strategies. It furnishes an efficacious tool for managing the stability of offshore wind farm grid systems and showcases the potential of meta-heuristic algorithms in optimizing power system stability. Despite these advancements, certain limitations remain:

The model established herein represents a first-order Taylor expansion small-signal model at a steady-state operating point, omitting higher-order terms. While it effectively describes the system's dynamic behavior, it may not encompass all nonlinear characteristics or the various disturbances encountered in real operation. Future research could consider incorporating more comprehensive and detailed models, incorporating additional nonlinear factors and real-time fluctuations in the environment and operating conditions, to enhance the model's authenticity and applicability.

Furthermore, while this identified the best-performing algorithm for the current model through comparison, it does not delve into the underlying mechanisms that contribute to performance of the GWO algorithm in this model. In the future, it will be necessary to explore and develop more efficient optimization algorithms, particularly those equipped to tackle large-scale, high-dimensional optimization problems.

Acknowledgements

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