

The Robustness Collaborative Design of Hydraulic Clutch Based on Multi-Dimensional Parameter Sensitivity Analysis

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1. Introduction

The electro-hydraulic clutch is widely used in vehicle and equipment, with increasing demands on its response speed and control accuracy. Consider the clutch used for gear shifting or power line switching in a vehicle, to achieve rapid and smooth engagement/disengagement, the hydraulic control device must complete the transition process within 0.2 seconds, ensuring pressure stable and precise [1]. This hydraulic system involves time-varying parameters and discontinuous states, its dynamic response is further complicated by factors such as the oil characteristics and multi-physics (mechanical-electrical-hydraulic) coupling, making the design of the multi-dimensional parameter set challenging. Exploring the stable domain of the system within the multi-dimensional parameter set and identifying the parameter set that optimizes response are key steps to enhance the dynamic response performance.

In research on enhancing the smoothness of clutch engagement and disengagement, multiple approaches have been extensively discussed, including structural parameters and control strategy optimization. Ouyang [2] developed a robust shift controller for heavy-duty automatic transmissions that integrates feedforward, feedback, and disturbance suppression for the parameters and operating uncertainties, effectively reducing shift shock and error. Lazar [3] adopted a model-based approach, creating an electro-hydraulic model that accounts for the coupling between the valve, cavity, and piston, and subsequently a model predictive controller was designed. Wang [4] proposed an adaptive fuzzy iterative control strategy to identify and compensate for typical deviations during the clutch filling process. Chung [5] employed differential flatness-based control to precisely govern electromagnetic actuator behavior. Collectively, these studies have led to significant improvements in control accuracy and system robustness.

Moreover, the dynamic response of the hydraulic control system, encompassing speed, stability, and oscillation, is highly sensitive to its structural parameters [6]. Yaobao [7] analyzed the dynamic characteristics of a relief valve by the classical control theory, taking stability, rapidity, and immunity into consideration, then revealed the underlying mechanism of how parameters affect the characteristics. Algorithms like the Genetic Algorithm (GA) have been employed for parameters optimization to balance efficiency, accuracy, and comfort in electro-hydraulic systems [8].

However, GA is known for slow convergence, a

tendency to get trapped in local optima and sensitivity to hyperparameters [9]. Tian [10] employed the Artificial Bee Colony (ABC) algorithm to optimize the parameters of the clutch in heavy automatic transmissions to shorten shifting time. However, the search efficiency of the ABC algorithm is constrained by the random perturbation mechanism and roulette wheel selection strategy, which may result in exploration redundancy and convergence oscillations [11]. Moreover, the convergence speed of the ABC algorithm is sensitive to population size, requiring the optimal hyperparameters to be determined through trial-and-error methods, thereby increasing the cost of engineering parameter tuning [12]. In contrast, GWO demonstrates superior average convergence performance and success rate compared to GA, DE, and PSO for problems with fewer than 30 dimensions, while minimizing the variance of the optimized trajectory [13].

Current methodologies for analyzing the stability of multidimensional parameters in nonlinear dynamic systems often employs linearization within a small domain, followed by the application of classical control theory- an approach misaligned with the intrinsic nonlinearity of proportional electro-hydraulic systems. Additionally, there are shortcomings to be improved in optimization algorithms.

Therefore, to address these above issues, based on the nonlinear dynamic numerical model of the system, this paper uses numerical methods to explore the boundary of the system's stable domain in multivariate parameter space. Furthermore, GWO algorithm is introduced to search for the optimal solution for heavy-duty clutch actuators in the parameter space. The structure of this paper is arranged as follows: Firstly, a nonlinear dynamic numerical model of the hydraulic system is established, and the EFAST method is adopted to identify the parameters that significantly impact the performance; Further the boundaries of the stable domain are explored; The Grey Wolf optimization algorithm is used to optimize the key parameters, and the optimization results are verified through virtual tests and experiments on test rig.

2. Mathematical Modeling

Fig. 1 illustrates the clutch hydraulic control system, comprising the proportional solenoid valve, mechanical pressure reducing valve, and clutch. The proportional solenoid valve generates pilot control pressure to adjust the mechanical pressure reducing valve's control chamber pressure P_{pilot} . The pilot pressure P_{pilot} controls movement of the

valve core horizontally within the valve body (with the positive direction of x_v defined to the right). Forces acting on the valve core include spring force $\sum F_s$, hydraulic force $\sum F_{flow}$, feedback chamber pressure P_{fb} , valve core motion damping force, and the contact force between core and valve body. The movement of the core adjusts the conduction state between the oil supply chamber P_{line} , the oil discharge chamber P_{out} , and the control chamber P_c , thereby enabling controlled clutch charging or discharging.

This paper analyzes the valve core and piston motion processes and based on the mathematical relationship between flow rate and pressure, establishes the pressure-flow equations for each chamber. Additionally, dynamic motion equations for the valve core and piston are derived to describe the nonlinear dynamic system.

2.1. Pilot valve pressure

$$P_{pilot} = K \cdot \frac{V}{R}, \quad (1)$$

here K is the proportionality coefficient, and V and R

represent the coil voltage and resistance, respectively [14].

2.2. Pressure reducing valve pressure

As illustrated in Fig. 1, the horizontal pressure exerted on the valve core of the pressure-reducing valve includes both the control chamber pressure and the feedback chamber pressure.

$$\sum F_p = P_{pilot} A_{pilot} - P_{fb} A_{fb}, \quad (2)$$

where A_{pilot} and A_{fb} represent the active areas of the control cavity and the feedback cavity, respectively.

The spring force exerted on the valve core can be expressed as:

$$\sum F_s = -k_1 x_0 - k_1 x_v, \quad (3)$$

where k_1 denotes the stiffness of the feedback chamber spring, and x_0 represents the initial compression of the spring.

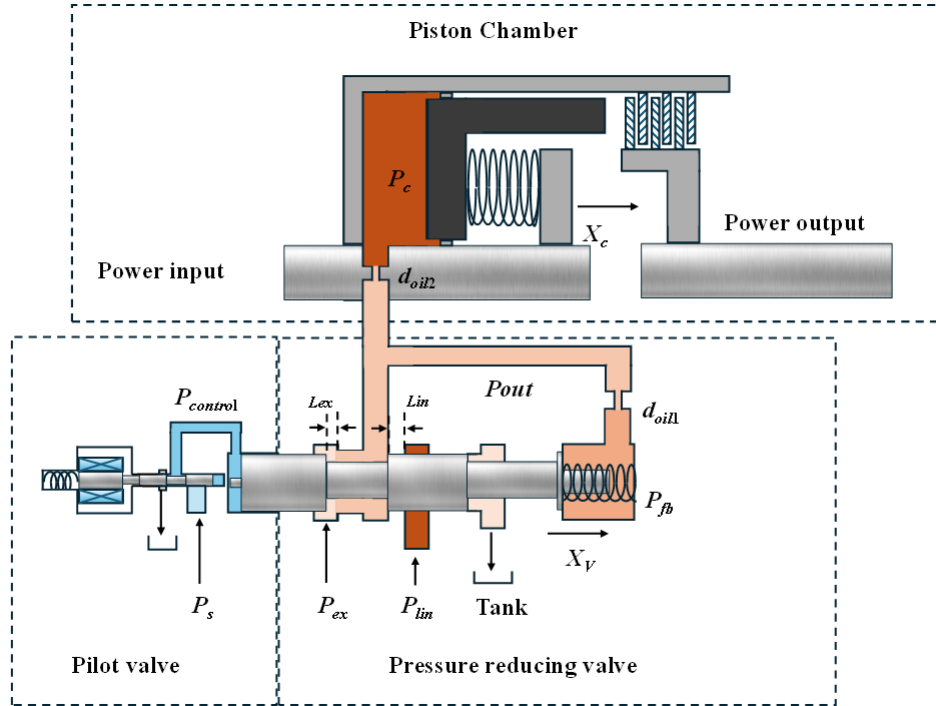


Fig. 1 Schematic diagram of clutch structure

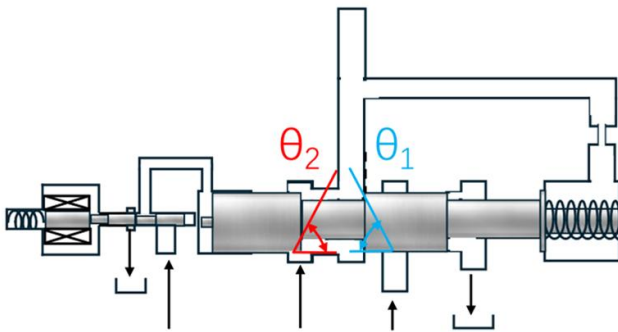


Fig. 2 Schematic diagram of jet angle

The hydraulic force exerted by the inlet and outlet flow rates acts horizontally on the valve core and can be derived from:

$$\sum F_{flow} = -2C_d A_{in} \cos \theta_1 (P_{line} - P_{out}) - 2C_d A_{ex} \cos \theta_2 (P_{line} - P_{out}), \quad (4)$$

where θ_1 and θ_2 represent the angles between the direction of oil flow and the direction of valve core movement (Fig. 2), C_d is the discharge coefficient, and A_{in} and A_{ex} are the inlet and outlet flow areas, respectively. The specific calculation is as follows:

$$\begin{cases} A_{in} = \pi d_v \times f_{in}(x_v) \\ A_{ex} = \pi d_v \times f_{ex}(x_v) \end{cases}, \quad (5)$$

where d_v represents the diameter of the valve core.

As shown in Fig. 3, the valve spool with triangular throttling grooves has a nonlinearly varying flow area. The hyperbolic tangent function $\tanh$ is adopted to fit $f(x_v)$ and suppress numerical oscillations induced by abrupt flow area jumps [15]. The expression is:

$$\begin{cases} f_{in}(x_v) = \frac{\tanh[1000(x_v - L_{in}) + 1]}{2(x_v - L_{in})} \\ f_{ex}(x_v) = \frac{\tanh[1000(L_{ex} - x_v) + 1]}{2(L_{ex} - x_v)}, \\ 0 \leq x_v \leq x_{v-max} \end{cases}, \quad (6)$$

where L_{in} and L_{ex} represent the positive overlap of the inlet and the load overlap of the outlet, respectively. When the displacement x_v of the valve core exceeds L_{ex} the oil outlet closes, and the flow function $f_{ex} = 0$. When x_{v-max} exceeds L_{in} , the inlet gradually opens, corresponding to $f_{in} > 0$. The entire range of motion of the valve core is limited by its maximum stroke x_{max} .

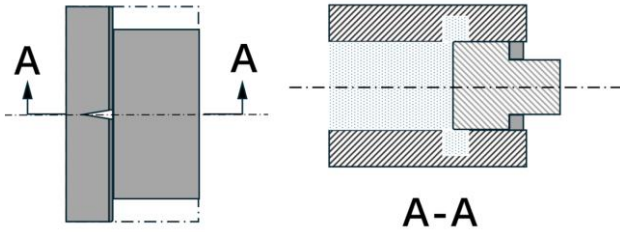


Fig. 3 Valve core (triangular throttling groove)

The interaction between the valve core and the valve body is modeled as a damped elastic collision.

$$F_c = k_{con} |x_{pen}| + k_r \dot{x}_{pen} (1 - e^{-|x_{pen}|/P_{en}}), \quad (7)$$

$$\begin{aligned} x_{pen} = & \frac{\tanh[1000(x_v - x_{max}) + 1]}{2(x_v - x_{max})} + \\ & + \frac{\tanh[1000 \times (-x_v) + 1]}{2x_v}, \end{aligned} \quad (8)$$

where k_{con} is the contact stiffness coefficient, x_{pen} is the penetration depth of the material, and its absolute value is taken to ensure that the contact force always points in the direction that reduces penetration. k_r is the coefficient of restitution, which is related to the rate of change in penetration depth $\dot{x}_{pen}$. P_{en} is the maximum allowable penetration depth.

The equation accounts for the states $x_v > x_{v-max}$ and $x_{v-max} < 0$ at the left and right ends. To address the discontinuity in material penetration depth at the critical state, this paper employs the hyperbolic tangent function to facilitate a smoother transition. The motion equation of the valve core

is expressed as:

$$\sum F_p + \sum F_s + \sum F_{flow} - F_c = m_v \ddot{x}_v + c_v \dot{x}_v, \quad (9)$$

where m_v represents the mass of the valve core, and c_v represents the damping coefficient.

2.3. Flow rate calculation

$$Q_{in} = C_d A_{in} \sqrt{\frac{2}{\rho} |P_{in} - P_{out}|} \times \text{sign}(P_{in} - P_{out}), \quad (10)$$

$$Q_{ex} = C_d A_{ex} \sqrt{\frac{2}{\rho} |P_{out} - P_{ex}|} \times \text{sign}(P_{out} - P_{ex}), \quad (11)$$

$$Q_{fb} = \frac{1}{4} C_d \pi d_{oil1}^2 \sqrt{\frac{2}{\rho} |P_{out} - P_{fb}|} \times \text{sign}(P_{out} - P_{fb}), \quad (12)$$

$$Q_c = \frac{1}{4} C_d \pi d_{oil2}^2 \sqrt{\frac{2}{\rho} |P_{out} - P_c|} \times \text{sign}(P_{out} - P_c), \quad (13)$$

where Q_{in} , Q_{ex} , Q_{fb} , Q_c represent the flow rates at the inlet, outlet, feedback chamber, and piston chamber, respectively; d_{oil1} , d_{oil2} represent the damping orifice diameters, and ρ represents the oil density.

Assuming zero radial clearance between the valve core and the valve body, the pressure buildup process in the output, feedback, and piston chambers can be expressed as follows.

$$\frac{V_{out}}{E_p} \dot{P}_{out} = Q_{in} - Q_{ex} - Q_{fb} - Q_c, \quad (14)$$

$$\frac{V_{fb}}{E_p} \dot{P}_{fb} = (Q_{fb} + A_{fb} \dot{x}_v), \quad (15)$$

$$V_{fb} = V_{fb0} - A_{fb} x_v, \quad (16)$$

where V_{out} represents the volume of the output chamber, V_{fb0} represents the initial volume of the feedback chamber at $x_v = 0$, and E_p denotes the effective elastic modulus of the oil.

Oil effective elastic modulus oil can be described as:

$$E_p = \frac{\beta(1+r_v)}{1 + \left(\frac{P_a}{p + P_a} \right)^{1/\kappa} \cdot \frac{r_v \beta}{\kappa(p + P_a)}}, \quad (17)$$

where β denotes the bulk modulus of the hydraulic oil, r_v represents the air-to-oil volume ratio, κ is the adiabatic index of air, P_a denotes the atmospheric pressure, and p represents the absolute pressure within the chamber.

2.4. Calculation of piston chamber pressure

$$\dot{P}_c = (Q_c - A_c \dot{x}_p) \frac{E_p}{V_c}, \quad (18)$$

$$V_c = V_{c0} + A_c x_p, \quad (19)$$

where V_{c0} is the initial volume of the piston chamber, x_p is the piston displacement, and A_c is the piston area.

The dynamic equation of piston motion is expressed as:

$$P_c A_c - F_{pre} - F_c = m_p \ddot{x}_p + c_p \dot{x}_p + k_p x_p, \quad (20)$$

$$\begin{Bmatrix} \dot{x}_v \\ \dot{v}_v \\ \dot{P}_{out} \\ \dot{P}_{fb} \\ \dot{x}_p \\ \dot{v}_p \\ \dot{P}_c \end{Bmatrix} = \begin{Bmatrix} v_v \\ f_2(x_v, v_v, P_{out}, P_{fb}, x_c, v_c, P_c), \text{ from (9)} \\ f_3(x_v, v_v, P_{out}, P_{fb}, x_c, v_c, P_c), \text{ from (14)} \\ f_4(x_v, v_v, P_{out}, P_{fb}, x_c, v_c, P_c), \text{ from (15)} \\ v_c \\ f_6(x_v, v_v, P_{out}, P_{fb}, x_c, v_c, P_c), \text{ from (20)} \\ f_7(x_v, v_v, P_{out}, P_{fb}, x_c, v_c, P_c), \text{ from (18)} \end{Bmatrix}. \quad (21)$$

3. Sensitivity Analysis

3.1. Objective Function

In this study, a weighted combination of two variables is utilized as the objective function to evaluate the system's response performance. It is defined as:

$$\begin{cases} J = \alpha \cdot \text{ITAE} + \beta \cdot T \\ \text{ITAE} = \int_0^T t \cdot |e(t)| dt \end{cases} \quad (22)$$

where J denotes the weighted objective function, and α and β represent the weighting coefficients corresponding to the ITAE and the system response time T , respectively. In this study, $\alpha = 0.3$ and $\beta = 0.7$ are adopted.

The control chamber pressure error is normalized to improve numerical stability and account for pressure scale differences. It is expressed as:

$$e(t) = \frac{P_c - P_c(\infty)}{P_c(\infty)}, \quad (23)$$

where $e(t)$ is the error function, P_c is the system output pressure, and $P_c(\infty)$ is the final steady-state pressure. In recent years, the Integral of Time-weighted Absolute Error (ITAE) has been widely used for PID parameter optimization [17]. To enhance system response speed, Das [18] proposed a weighted combination of ITAE with other performance indicators, such as control signals, for optimization. Furthermore, Gulgonul [19] incorporated response time into the optimization objective of the SOSTIAE method based on ITAE, demonstrating the effectiveness of concurrently designing error and dynamic performance indicators. Therefore, the weighted combination method adopted in this study is grounded in a robust theoretical framework.

According to reference [20], the EFAST method has been established as a reliable and robust global sensitivity analysis technique. It can generate sensitivity coefficients of various orders, enabling the evaluation of coupling

where F_{pre} is the spring force under initial conditions; m_p is the mass of the piston; k_p is the spring stiffness; c_p is the damping coefficient, which has been experimentally measured by Jian et al [16].

In summary, the behavior of the clutch hydraulic control system can be expressed as the following system of equations to describe:

effects among multiple indicators. The method has been extensively utilized in large-scale models [21] and exhibits significant generalizability. Consequently, this study employs the EFAST method for sensitivity analysis.

3.1.1. EFAST global sensitivity analysis method

The EFAST method generates model inputs by mapping the input variables onto a sine function of the scan variable s . The formulation is as follows:

$$x_i = 0.5 + \frac{\arcsin[\sin(\omega_i s + \varphi_i)]}{\pi}, \quad (24)$$

where $x_i \in [0, 1]$ denotes the i -th normalized input variable; ω_i represents the scanning frequency; $\varphi_i \in [0, 2\pi]$ denotes the random initial phase; and $s \in [-\pi, \pi]$ is the unified scanning parameter.

The model response $y = f(s)$ can be expanded into a Fourier series and expressed as:

$$y = f(s) = \sum_{p=-\infty}^{\infty} A_p \cos(ps) + B_p \sin(ps), \quad (25)$$

$$A_p = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \cos(px) dx, \quad (26)$$

$$B_p = \frac{1}{\pi} \int_{-\pi}^{\pi} f(x) \sin(px) dx, \quad (27)$$

$$A_p = A_p^2 + B_p^2 \quad (p \in Z = -\infty, \dots, -1, 1, \dots, \infty), \quad (28)$$

$$V_i = \sum_{p \in Z} A_p \omega_i = 2 \sum_{p=1}^{\infty} A_p \omega_i, \quad (29)$$

where $p \in Z$ represents the Fourier transform parameters; A_p and B_p denote the Fourier amplitudes; A_p is the power spectrum corresponding to each frequency order; and V_i denotes

the output variance induced by each input parameter x_i .

The total variance of the model output, which represents the overall uncertainty caused by all input parameters, can be expressed as:

$$V = \sum_{p \in Z} A_p = 2 \sum_{p=1}^{\infty} A_p. \quad (30)$$

The total variance of the model can be decomposed as:

$$V = \sum_{1 \leq i \leq k} V_i + \sum_{1 \leq i < j \leq k} V_{i,j} + \dots + V_{12 \dots k}, \quad (31)$$

where V_i denotes the variance induced by variations in parameter x_i ; V_{ij} represents the variance arising from the interaction between parameters x_i and x_j ; and $V_{12 \dots k}$ corresponds to the variance resulting from the interactions between parameter x_i and the remaining $k-1$ parameters.

The first-order sensitivity coefficient can be expressed as:

$$S_i = \frac{V_i}{V}. \quad (32)$$

The global sensitivity coefficient can be expressed as:

$$S_{ri} = \frac{V - V_{-i}}{V}, \quad (33)$$

where V_{-i} represents the total variance of the system when parameter x_i is excluded.

3.1.2. Analysis

The parameters utilized in the simulations are listed in Table 1. The parameters that may significantly influence the objective function are listed in Table 2 and the sampling points of each parameter are uniformly distributed within their respective threshold ranges.

Saltelli [22] stated that the total number of sampling points for the EFAST method should be $N_w K$, where

Table 1

Nominal system parameters used in simulation.

Notation	Description	Value	Unit
K	proportional coefficient	1×10^6	—
A_{pilot}	Areas of the control cavity	2.32×10^{-4}	m^2
A_c	Piston area	2×10^{-3}	m^2
A_{fb}	Feedback cavity	1.36×10^{-4}	m^2
θ_1	Jet angle	68	$^\circ$
θ_2	Jet angle	68	$^\circ$
C_d	discharge coefficient	17	—
c_v	Damping coefficient	16	$\text{N} \cdot \text{s/mm}$
d_{oil1}	feedback cavity damping orifice diameter	2	mm
d_{oil2}	piston cavity damping orifice diameter	5	mm
ρ	Oil density	797.8	kg/m^3
E_P	Elastic modulus	2×10^9	Pa
F_{pre}	Spring force under initial conditions	200	N
κ	adiabatic index of air	1.4	—
k_{con}	Contact stiffness coefficient	5×10^6	N/m
k_r	Penalty damping coefficient	5×10^4	$\text{N} \cdot \text{s/m}$
k_1	Stiffness of the feedback chamber spring	6	N/mm
k_p	Stiffness of the piston chamber spring	2000	N/mm
L_{in}	positive overlap	3.6	mm
L_{ex}	load overlap	2.6	mm
m_v	the mass of the valve core	0.015	kg
m_c	the mass of the piston	0.1	kg
P_a	atmospheric pressure	1.05×10^5	Pa
P_{in}	Inlet pressure	4×10^6	Pa
P_{en}	Maximum penetration depth of the spool	0.001	m
P_{enc}	Maximum penetration depth of the piston	0.01	m
V_{out}	the volume of the output chamber	5×10^{-4}	m^3
V_{fb0}	Initial volume of the feedback chamber	1×10^{-5}	m^3
V_{c0}	Initial volume of the piston chamber	9×10^{-2}	m^3
x_0	the initial compression of the spring	8	m^3
x_{v-max}	Maximum stroke of the valve spool	5	mm
x_{c-max}	Maximum stroke of the piston	10	mm

N_w denotes the base number of sampling points for each parameter and K represents the dimensionality of the parameter space. When estimating the first-order and total sensitivity coefficients, $N_w \geq 512$ is recommended. Based on the geometric parameter ranges listed in Table 2 the Monte Carlo method was employed to sample the geometric parameters, with the base sampling number set to $N_w = 625$. A total of 5000 simulations were conducted.

The results are represented in Fig. 4. Comparison of the two analyses reveals that L_{in} has the most significant influence. Its first-order and total global sensitivity coefficients are 73.61% and 82.65%, respectively, indicating that L_{in} plays a dominant role. V_{out} and d_{oil2} also demonstrate high sensitivity coefficients, ranking second in both first-order and total sensitivity indices. The importance of optimizing other low-sensitivity parameters is comparatively minor. In summary, L_{in} , d_{oil2} , and V_{out} are the primary parameters affecting the response performance of the hydraulic system. Consequently, this study focuses on optimizing the system parameters concerning these three parameters to enhance the dynamic characteristics of the clutch hydraulic control system while ensuring stability constraints are satisfied.

Table 2

Parameter input for sensitivity analysis

Name	Min	Max	Unit
θ_1	47.6	88.4	°
L_{in}	2.52	4.68	mm
m_v	0.0105	0.0195	kg
m_p	0.07	0.13	kg
d_{oil1}	1.4	2.6	mm
d_{oil2}	3.5	6.5	mm
V_{out}	3.5×10^{-5}	6.5×10^{-4}	m^3
V_{fb0}	7×10^{-4}	1.3×10^{-3}	m^3

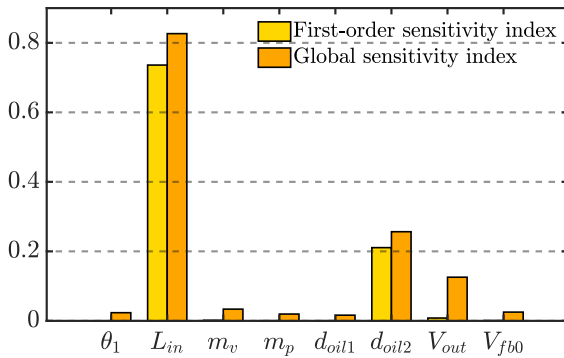


Fig. 4 Normalized sensitivity analysis index

4. Optimization of Structural Parameters

In recent years, inspired by collective intelligence behaviors observed in nature, numerous efficient intelligent optimization algorithms have been developed. Among them, the Grey Wolf Optimizer (GWO), proposed by Mirjalili et al. [23] 2014, is a swarm intelligence algorithm inspired by the social hierarchy and hunting mechanisms of grey wolves. Owing to its simple parameter settings, gradient-free characteristics, and strong global search capability, GWO has demonstrated high accuracy and stability in solving nonlinear optimization problems. Previous studies have confirmed

its effectiveness in various engineering applications, including mechanical structure optimization and nonlinear parameter design [24, 25]. Furthermore, its ability to handle complex optimization problems with multiple constraints makes it suitable for parameter optimization in engineering systems [26].

In this study, the dynamic characteristics of the counterbalance valve-controlled hydraulic system are significantly influenced by multiple structural parameters, and the nonlinear relationships between these parameters and system performance are difficult to establish analytically. Therefore, the GWO algorithm is employed to optimize the key structural parameters of the system, aiming to improve its dynamic performance and achieve an optimal design.

4.1. Exploration of Stable Domain Boundaries

Optimization of the response performance of the clutch hydraulic control system requires stability as a critical constraint. To investigate the stable domain boundaries of the system within the three-dimensional parameter space defined by L_{in} , d_{oil2} and V_{out} , a parameter scanning method was employed for virtual computational analysis. Initially, a time-sliding window with appropriate length was selected. Oscillation feature detection was performed on the signal within the window, significant peaks and valleys were extracted, leading to significance threshold of valve core displacement oscillation was set to $2 \times 10^{-6} m$. The detection of multiple peaks and valleys within the sliding window indicates sustained and pronounced oscillatory behavior, and the system is classified as unstable.

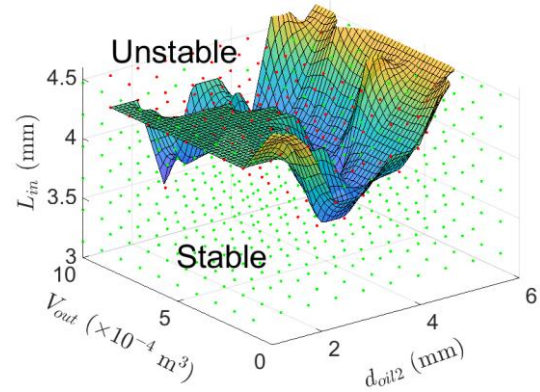


Fig. 5 Boundary of stable domain

Following the criterion [27], an automated search for the stable domain boundary was conducted. After more than 1000 virtual simulations, the stable domain boundary of the system within the three-dimensional parameter space defined by L_{in} , d_{oil2} and V_{out} was obtained, as shown in Fig. 5. The stable domain boundary serves as a constraint for parameter optimization, ensuring system stability during performance optimization. The stable domain boundary of the parameter space, as shown in Fig. 5, can be expressed as follows:

$$f(V_{out}, L_{in}, d_{oil2}) \geq 0. \quad (34)$$

Due to a damping orifice smaller than 1 mm is prone to blockage and difficult to manufacture, and one larger than 6 mm weakens the throttling effect and reduces damping, the value of d_{oil2} is determined accordingly.

$$1 \leq d_{oil2} \leq 6. \quad (35)$$

The control logic governing the inlet and outlet openings requires that the two channels cannot be opened simultaneously. Consequently, a physical dead zone of 0.2 mm is established between the two channels. The design range of L_{in} is defined as follows:

$$2.8 \leq L_{in} \leq 5. \quad (36)$$

Based on the above analysis, the problem can be summarized as follows:

$$\begin{cases} \min J & , \text{ from (22)} \\ f(V_{out}, L_{in}, d_{oil2}) \geq 0, & \text{ from (34)} \\ 1 \leq d_{oil2} \leq 6 & , \text{ from (35)} \\ 2.8 \leq L_{in} \leq 5 & , \text{ from (36)} \end{cases} \quad (37)$$

4.2. Parameter optimization

In this study, the weighted objective function J is used as the fitness function, with the position of each grey wolf defined as $t = [d_{oil2}, V_{out}, L_{in}]$. In each iteration, the parameters are input into the mathematical model for a 1-second simulation to calculate J and the stability criterion f . If the stability constraint is satisfied, J is assigned as the fitness value; otherwise, the position is deemed invalid and given a large penalty (10^6) to eliminate infeasible solutions.

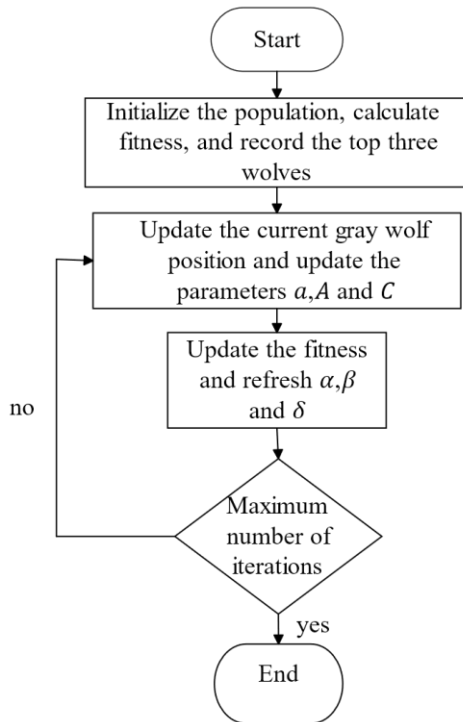


Fig. 6 Flowchart of the Gray Wolf Algorithm

4.3. Optimization analysis

The maximum number of iterations for GWO is set to 70, with a population size of 20. These settings follow similar hydraulic system optimization studies [23], balancing computational cost and convergence accuracy.

As shown in Fig. 7, the algorithm demonstrates

favorable convergence during parameter optimization process. In the initial 10 iterations, the objective function declines rapidly from 0.0632 to below 0.048, reflecting strong global search capability. Between the 10th and 20th iterations, it decreased gradually and stabilized, indicating entry into the local search phase. From the 30th iteration onward, the function remained around 0.0411, showing convergence and negligible further improvement. The optimization results are summarized in Table 3.

Table 3

Optimization results

	L_{in}	d_{oil2}	V_{out}	J
Without optimization	3.6	5	0.5	0.0632
Optimization	2.8	4.8	0.2283	0.0411
Unit	mm	mm	L	s

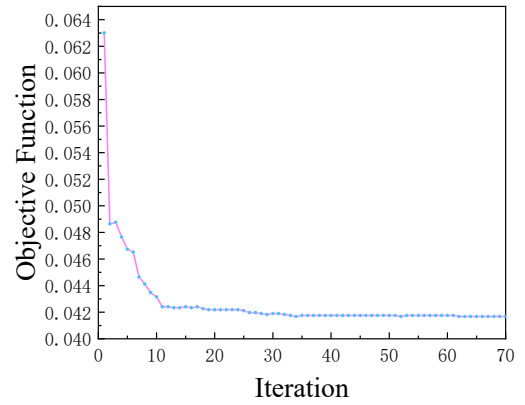


Fig. 7 Change in the objective function

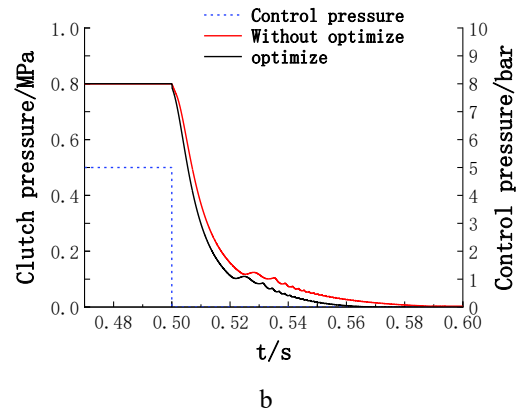
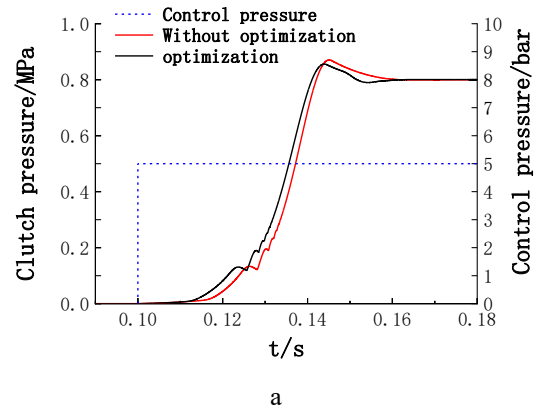


Fig. 8 Simulation of the piston chamber pressure dynamics (time step: 0.0001 s): a – comparison of rise time, b – comparison of fall time

To assess the effectiveness of the parameter optimization in enhancing the system's dynamic performance, this study compares the system responses before and after optimization under identical initial conditions and excitation. Fig. 8 illustrates the time-history response of the clutch piston chamber pressure. The optimized system exhibits a significantly faster response speed. The optimization results achieve a balance between dynamic and steady-state performance while satisfying stability constraints, thereby demonstrating the strong engineering applicability and robustness of the proposed optimization algorithm and stability criteria. These results further confirm the critical importance of parameter selection and optimization algorithms in improving overall system performance.

5. Experiment

5.1. Experimental setup and working principle

Fig. 9 shows the schematic diagram of the electro-hydraulic control test bench. The test bench mainly consists of three parts: the hydraulic power circuit, the electro-hydraulic control module, and the data acquisition and communication system. The hydraulic tank provides the working medium for the system, and the hydraulic pump delivers pressurized oil into the test circuit to supply the required flow rate and pressure for the actuating components. The electro-hydraulic control module receives control signals from the ECU and drives the valve group to achieve hydraulic circuit switching and regulate the system pressure and flow rate.

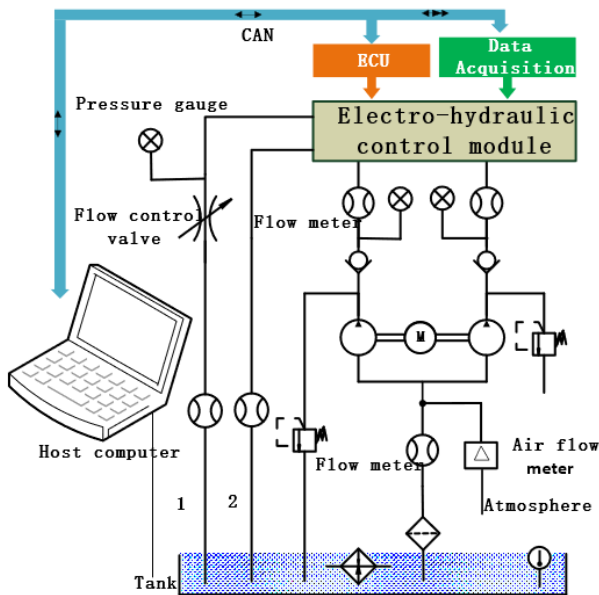


Fig. 9 Schematic diagram of the test bench

During the experiment, pressure sensors and flow meters installed in the hydraulic circuit were used to measure the variations in system pressure and flow rate, respectively. Meanwhile, a gas flow meter was employed to monitor the airflow characteristics in the ventilation branch. The data collected by the sensors were processed through the data acquisition unit and transmitted to the host computer via the CAN bus for subsequent analysis. A flow control valve was installed in the test circuit to regulate the load

conditions, while a relief valve was used to limit the maximum system pressure and ensure the safety of the experimental process.

5.2. Experimental results and discussion

To verify the effectiveness of the proposed optimization method, experiments were conducted using the original and optimized parameters. The dynamic response characteristics were evaluated by applying step control signals through the pilot solenoid valve.

Fig. 10 shows the pressure responses under step pressurization and depressurization conditions. During pressurization, a 5 bar control signal was applied at 10.05 s. In the pre-filling stage (10.05–10.10 s), the original system exhibited periodic pressure fluctuations, while the optimized system showed a smoother response with reduced pressure pulsation. When approaching the steady-state pressure of 0.8 MPa, the original system presented overshoot and oscillations, whereas the optimized system achieved a faster and smoother pressure rise.

During depressurization, the pressure release command was applied at 10.95 s. Although both systems exhibited similar initial pressure decay trends, the original system showed slower pressure attenuation and a longer stabilization time in the later stage. The optimized system achieved a smoother pressure release process with reduced low-pressure fluctuations.

The experimental results showed consistent trends with the simulation results, verifying the effectiveness of the proposed optimization method. The deviations between

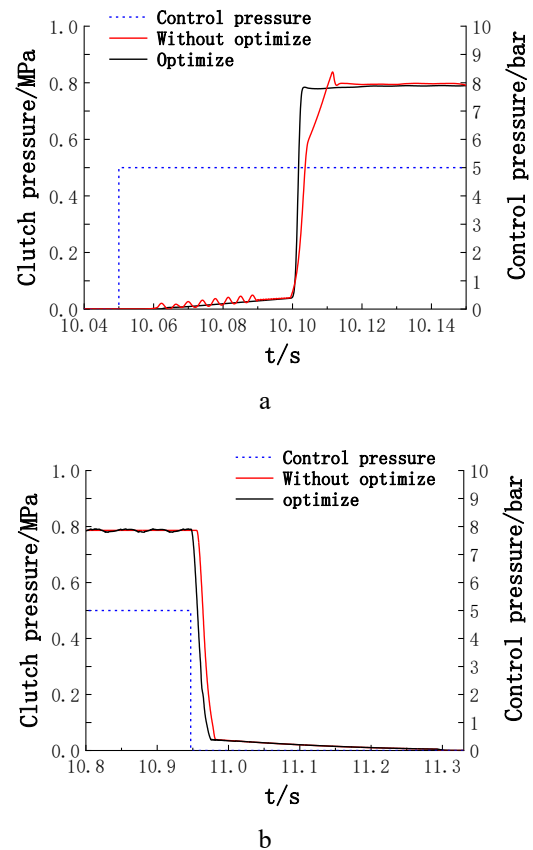


Fig. 10 Experimental results of the piston chamber pressure over time: a – comparison of rise time, b – comparison of fall time

simulation and experiment are mainly attributed to manufacturing tolerances of hydraulic components, internal leakage, pipeline pressure losses, model simplifications of friction and pressure loss, as well as measurement errors and control delays.

6. Conclusions

This study analyzed the motion of the valve core and piston and established a nonlinear dynamic mathematical model to describe the system, based on the mathematical relationship between flow rate and pressure. A sensitivity analysis of key system parameters was conducted using the EFAST method. The results revealed that the positive overlap at the inlet, L_{in} had the greatest influence on the objective function, followed by d_{oil2} and the output chamber volume V_{out} .

The boundaries delineating stable and unstable regions were determined using the parameter scanning method and incorporated as stability constraints in the optimization process. Furthermore, while ensuring system stability, the GWO was utilized to optimize the parameters, with the weighted objective function of response time and pressure deviation serving as the optimization criterion.

The simulation results show that, with stability-constrained optimized parameters, the system's rising response time under step excitation is 55 ms, approximately 11.2% shorter than that before optimization. The descending response time is approximately 62ms, representing an 18% reduction compared with the unoptimized structure, thereby enhancing the smoothness and quality of the automatic transmission shifting process. Further experimental verification of the hydraulic control system was conducted on the test bench. The results showed that the rising response time under step excitation was 58ms, approximately 7.9% shorter than that observed prior to optimization. The descending response time under step excitation was 70ms, about 14% shorter than that observed prior to optimization.

In summary, the method proposed in this study for exploring and optimizing the stability boundary significantly improves the dynamic response performance of the clutch hydraulic control system while maintaining system stability, demonstrating substantial engineering applicability and reference value. Future work will extend to analyzing the transmission system response and optimizing the pressure trajectory throughout the entire shifting process to achieve superior shift control performance.

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THE ROBUSTNESS COLLABORATIVE DESIGN OF HYDRAULIC CLUTCH BASED ON MULTI-DIMENSIONAL PARAMETER SENSITIVITY ANALYSIS

S u m m a r y

The response speed, accuracy, and stability of the hydraulic clutch are its key performance evaluation indicators. This study focuses on the stability and response quality of the hydraulic clutch, successively conducting mathematical description of physical mechanisms, global sensitivity analysis of multiple parameters, exploration of stability domain boundaries in multi-dimensional parameter spaces, and optimization of dynamic response characteristics. First, the mathematical model of characteristics such as the discontinuous nonlinearity in the flow area, valve core contact nonlinearity, and the nonlinearity of the oil bulk modulus were established. Upon this basis, a nonlinear dynamic mathematical model of the hydraulic clutch system was developed. Then, the Extended Fourier Amplitude Sensitivity Test (EFAST) method was employed, using the weighted objective function of response time and pressure deviation within the clutch as an observation index, followed by sensitivity analysis of the multi-dimensional parameter set. Several parameters with highest sensitivity were selected to construct an optimization framework constrained by the boundaries of the stable domain. The Grey Wolf Optimization Algorithm (GWO) was utilized for parameter optimization and solution. The optimization results demonstrate that, within the stable domain of the parameter set, the optimized structural parameters improve the pressure rise rate of the clutch by approximately 11.2% and the pressure drop rate by approximately 18%. This method offers significant support for enhancing and designing the response performance of the hydraulic clutch system.

Keywords: hydraulic control system, stability domain, response time, sensitivity analysis, Grey Wolf Optimization algorithm.

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