

RESEARCH ARTICLE

Multi-objective optimization of parallel hydraulic flushing circuit based on NSGA-II

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Abstract - In the parallel flushing circuit for large-scale hydraulic motor testing, increasing flushing flow rate raises total pressure loss and casing pressure differential, while reducing pipeline pressure loss alone increases casing pressure. To solve this strongly conflicting engineering problem, this paper proposes an optimization method combining Maximin Latin Hypercube Sampling, Kriging surrogate model and NSGA-II algorithm. Specifically, five core design variables (pipeline lengths, elbow quantities, and pump flow) are systematically tuned to minimize casing pressure difference, minimize total pressure loss, and maximize flushing flow. The TOPSIS method is further applied to derive optimal solutions under different design preferences. The method was verified via AMESim simulation and leave-one-out cross-validation, achieving 0.8%–10.1% optimization for each target, and provides a valuable engineering reference for multi-objective optimization of similar hydraulic circuits. In conclusion, the proposed multi-objective optimization framework successfully resolves the inherent physical contradiction between casing heat dissipation and mechanical seal safety. It proves that combining MLHS, Kriging surrogate models, and NSGA-II is a highly robust approach for large-scale hydraulic test bench design.

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1. Introduction

Large-scale hydraulic motors, characterized by high torque, low speed, and precise transmission control, are finding increasingly widespread applications in engineering fields such as loaders, mining equipment, and marine vessels [1]–[2]. Consequently, the testing of large-scale hydraulic motors after production and assembly plays a crucial role in ensuring their reliability during long-term, high-intensity operation under harsh working conditions. Taking the testing of Hägglunds large-scale internal curve radial piston hydraulic motors as an example, this study focuses on the flushing circuit that removes a large amount of heat and metal debris generated inside the motor casing during the testing process; the overall optimization of this circuit is of great significance for the testing of large-scale hydraulic motors, which can last for several weeks.

Due to the long test cycle and high-test power of large-scale hydraulic motors, the adoption of traditional testing methods will inevitably consume a huge amount of electrical energy during the test, leading to a sharp increase in test costs. In response to this characteristic, a dual-motor torque-opposing mode is adopted in the testing process: the torque generated by the tested hydraulic motor during the test is transmitted to the main shaft of another hydraulic motor of the same model through the central shaft, which is called the loading motor. This method not only creates and simulates the load in actual use for the tested motor, but also allows the loading motor to be used as a hydraulic pump to convert the torque generated by the tested motor back into electrical energy and feed it into the test power grid [3]. This dual-hydraulic-motor torque-opposing testing method significantly reduces the energy consumption cost during the entire test period and has become a scheme for large-scale hydraulic motor testing. The 3D schematic diagram of the test bench is shown in Figure 1 (a).

Although the dual-motor torque-opposing testing method is beneficial for reducing test costs, the accompanying problems have also emerged. Although the loading motor operates as a hydraulic pump during the test, it still requires a separate flushing circuit to cool and flush its casing. Due to the large number and high complexity of the entire test bench system, the simple arrangement of the flushing circuit is prone to excessive pressure loss and unbalanced pressure between the two motor casings. Moreover, unlike the motor's piston chamber, the internal casing of the piston motor cannot withstand excessive pressure. As a sealing component, the maximum pressure that the shaft seal can withstand is relatively low (the pressure resistance of the shaft seal for this test model should not exceed 3bar). Secondly, poor flushing conditions [4], and relatively high pressure [5] will have an adverse impact on the service life of the sealing components. In addition, due to the design factors of the test bench, the relative pressure difference between the two motor casings is more likely to cause accelerated wear and premature failure of the sealing components under the condition of long-term testing [6]. Since the loading motor is part of the test bench, the above-mentioned problems are more likely to occur when replacing different tested motors and conducting long-term tests under different working conditions. To sum up, the optimization of the hydraulic flushing circuit for this large-scale hydraulic motor test bench is of great importance.

In recent years, many scholars have conducted extensive research on the optimization of hydraulic circuits and the reduction of pressure loss. Among various components, elbows have become a key research focus due to their significant local resistance. In Reference [7], the author reduced the local resistance of elbows by innovatively designing the structure of elbows in hydraulic systems and conducting simulation analysis using simulation software. Recent research [8] has proposed integrating novel Double-Sharp guide vanes within hydraulic elbows to simultaneously address additive

manufacturing constraints and optimize internal flow fields. This structural innovation effectively disrupts large-scale vortices, achieving a 47.29% reduction in peak pressure drop and significantly lowering turbulent kinetic energy. Addressing the design complexities of additively manufactured hydraulic valves, scholars have developed a parametric mathematical model to rapidly predict pressure loss in curved internal channels [9]. By combining CFD simulations and experimental validation, this method accurately characterizes flow resistance with an error of 7.72%, significantly enhancing the design efficiency of hydraulic systems. Reference [10] conducted multiple test experiments on pipelines with different parameters and carried out quantitative research on the pressure loss at pipeline elbows. In addition, Reference [11] considered the turbulent flow state and all important conditions in the study of liquid flow in elbows, and optimized various parameters using genetic algorithms. The critical nature of pressure loss in hydraulic systems continues to drive cutting-edge research. For instance, recent studies have deeply investigated the microscopic fluid dynamics and fundamental mechanisms of hydraulic pressure loss under complex vertical transport conditions [12], further emphasizing the necessity of accurately mapping wall shear stress and local resistance in fluid networks. To quantify and mitigate energy inefficiencies in mobile hydraulic drives, recent studies utilized MATLAB SIMULINK to simulate pressure drops across complex pipeline networks [13]. Their analysis revealed that accurately optimizing the internal diameter of critical line segments can reduce frictional power loss by over 80%, providing a highly effective strategy for energy recovery and system efficiency improvement. To simplify the structure of multi-motor hydraulic systems, recent studies proposed a novel six-position six-way direction control valve and systematically evaluated its flow-pressure loss characteristics [14]. Experimental results indicated that the maximum pressure loss is highly dependent on the valve's specific operating positions and internal flow directions, highlighting the necessity of precisely evaluating localized resistance in complex hydraulic configurations.

For the hydraulic flushing circuit, timely removal of the heat generated by the hydraulic motor during testing is also one of its main functions. To mitigate thermal accumulation in continuous fluid recirculation of hydrostatic transmissions, recent studies [15] have optimized the design and control of hydraulic flushing circuits. By implementing an intelligent temperature-dependent control strategy for the flushing valve, the system dynamically regulates the flushing flow, effectively preventing overheating while significantly reducing overall energy losses. In the realm of advanced thermal management, recent research [16] has explored the efficacy of specialized microchannel heat sinks utilizing vertical fluid flushing and jet impingement. By systematically evaluating local heat transfer characteristics, studies confirm that targeted fluid flushing strategies can significantly enhance cooling efficiency and maintain surface temperatures within strict safety margins under high heat fluxes. Similarly, Reference [17] indicated that when a non-traditional oil cooling system is used, the volume flow rate of the cooling oil has a significant impact on heat dissipation. While these studies establish the importance of cooling flow, they often treat it as an independent control variable. A major conflicting operational trade-off in practical application is that indiscriminately increasing the flushing flow to enhance heat dissipation exponentially exacerbates the pipeline pressure loss—a severe physical contradiction that prior single-objective optimization studies have largely overlooked.

When optimizing hydraulic circuits, the use of simulation software can greatly facilitate the analysis of fluid flow in pipelines and subsequent optimization. To accurately evaluate the pressure drop and thermal-hydraulic characteristics within complex flow channels, recent studies [18] have extensively utilized advanced numerical simulation software. By incorporating real fluid property modules and robust turbulence models, computational simulations provide a highly reliable framework for analysing localized flow resistance and heat transfer under diverse boundaries and operating conditions. The AMESim software has proven to be an indispensable tool for analysing energy consumption and mitigating throttling losses in modern pump-controlled hydraulic circuits [19]. Utilizing this dynamic simulation environment, scholars have successfully modelled complex pressure behaviours under variable working conditions, providing a robust virtual testing ground that bridges the gap between theoretical algorithm design and physical experimental validation. Addressing the severe energy dissipation inherent in traditional hydraulic circuits, scholars [20] have proposed novel flow-sharing architectures aimed at minimizing wasted energy. Utilizing lumped parameter simulation environments such as AMESim, these studies successfully quantified the energy-saving potential and pressure loss reduction achieved by the optimized valve designs, further validating their industrial scalability. Additionally, Reference [21] combined AMESim with genetic algorithms to design a hydraulic control system, optimized the system's power loss through the algorithm, and improved the system's performance. The introduction of the optimization algorithm has been of great help in solving related problems. To tackle complex combinatorial optimization challenges in manufacturing scheduling, recent research [22] introduced the Teaching Learning-Based Optimization (TLBO) algorithm. Extensive computational experiments demonstrated that TLBO significantly outperforms traditional metaheuristic algorithms, such as Particle Swarm Optimization and Grey Wolf Optimizer, exhibiting superior search efficiency and the highest average performance ranking in minimizing comprehensive production costs. By leveraging an optimized algorithmic approach to conduct multi-time scale dispatch, researchers [23] achieved substantial reductions in total scheduling costs and a remarkable 13.98% improvement in system response speed, highlighting the robust capability of intelligent algorithms in enhancing system flexibility and economic benefits. To enhance the control accuracy and performance of electromechanical servo systems, recent research proposed an innovative dual-motor synchronized control algorithm [24]. This algorithmic optimization significantly improves the system's dynamic response and load control precision, demonstrating its effectiveness in advanced motor servo applications. Despite these advancements in algorithm application, a significant scalability issue arises when directly coupling 3D computational fluid dynamics (CFD) or 1D simulation software with heuristic algorithms. For large-scale hydraulic systems, this direct-coupling approach demands prohibitive computational costs and time during the massive iterative evaluation process, making it difficult to

scale up to complex multi-objective scenarios. Among them, the NSGA-II multi-objective optimization algorithm [25] is one of the optimal methods for solving related hydraulic circuit optimization problems, as it can address the issue of "synergistic optimization of multiple conflicting objectives", enable multi-angle objective optimization under multi-parameter conditions, and cover a wide range of parameter optimization combinations. Beyond hydraulic systems, the NSGA-II algorithm has demonstrated robust capability in resolving complex fluid-mechanical conflicts within other automotive applications. For instance, researchers [26] successfully applied NSGA-II to optimize vehicle exhaust mufflers, achieving an optimal Pareto balance between maximizing acoustic transmission loss and minimizing fluid pressure drop. Reference [27] suggests the NSGA-II multi-objective optimization algorithm was combined with a neural network to establish an optimization model; with pressure loss set as one of the optimization objectives, the pressure loss was reduced by 9.0% after optimization. Furthermore, Reference [28] proposed a new hybrid algorithm based on the NSGA-II multi-objective optimization algorithm to achieve better optimization of the target hydraulic system, and verified the effectiveness of this method in reducing the pressure loss of the target system.

Researchers have conducted detailed studies on hydraulic circuit optimization from various perspectives, covering both theoretical research and experimental testing. Recently, surrogate-assisted multi-objective optimization has become a prominent trend in fluid power systems due to its computational efficiency. This optimization trend is evolving rapidly in the latest literature. Recent advanced frameworks have successfully integrated computational fluid dynamics (CFD) with the NSGA-II algorithm to optimize the hydraulic performance of complex multiphase pumps [29], and applied genetic algorithms to balance hydraulic efficiency with broader economic and sustainability metrics [30]. Furthermore, to strictly ensure computational efficiency without sacrificing solution fidelity, highly precise Kriging surrogate models combined with novel intelligent algorithms are increasingly adopted to reduce performance fluctuations in multi-objective engineering tasks [31]. Several recent studies (2022-2024) have successfully applied Kriging, RBF, or ANN combined with NSGA-II to optimize individual hydraulic components, such as multi-way valves or single piping networks. Specifically, existing surrogate-model applications conventionally assume deterministic, fixed boundary conditions (e.g., a constant inlet flow rate). Therefore, they are fundamentally ill-equipped to adequately address the strongly coupled pressure-loss versus flow-rate conflict inherent in parallel circuits. In a parallel layout, modifying the geometric resistance of one branch does not merely alter its own localized pressure drop; it dynamically redistributes the flow across all constituent branches. This non-linear kinetic redistribution constantly shifts the operating points of the entire system, rendering conventional static surrogate mapping ineffective and necessitating a fully coupled multi-objective framework. However, a critical gap remains existing surrogate-based frameworks primarily focus on isolated, single-branch systems where objective conflicts are relatively straightforward. They fall short in addressing the highly coupled, asymmetric fluid dynamics inherent in large-scale parallel hydraulic test benches. In such parallel circuits, altering the geometry of one branch non-linearly redistributes the flow and amplifies the pressure differential across the entire system, creating a much stronger and more complex multi-objective conflict. To strictly justify the methodological shift from traditional single-objective approaches to a multi-objective framework, the physical outcomes of these algorithms must be contrasted. In highly coupled hydraulic circuits, single-objective pipeline optimization inevitably drives the system toward unacceptable operational extremes for instance, minimizing pressure loss by drastically reducing the flushing flow, which consequently causes thermal failure of the motor. Conversely, a multi-objective framework mathematically internalizes these physical contradictions. It captures the exact trade-off boundaries (Pareto front) between cooling capacity and seal safety, ensuring the optimization of one parameter does not cause the catastrophic degradation of another. Therefore, adopting a multi-objective methodology is not merely an algorithmic preference, but an engineering necessity for parallel flushing circuits. To bridge this gap, this paper does not merely apply existing algorithms but customizes a holistic surrogate-assisted framework specifically for the severe multi-objective conflicts in large-scale parallel flushing circuits. The original contributions of this study are threefold: We establish a highly accurate Kriging-based predictive model trained via MLHS, successfully decoupling the complex non-linear flow-pressure interactions in a parallel hydraulic layout; The study quantitatively reveals the underlying physical trade-off mechanisms between flushing cooling capacity and the mechanical safety boundaries of motor shaft seals, yielding a comprehensive Pareto optimal front; integrating the TOPSIS method, the framework provides a scalable parameter-selection strategy, allowing engineers to dynamically adapt the circuit design according to varying power loads and test duration requirements of different hydraulic motors. In this study, the AMESim simulation software and the NSGA-II multi-objective optimization algorithm are used to analyse and optimize the parallel hydraulic flushing circuit. The optimization aims to reduce the casing pressure of the two motors, reduce the casing pressure difference, and decrease the pressure loss of the two parallel flushing circuits, realizing multi-factor and multi-objective optimization to lower these values to a smaller range. In this framework, a mathematical model is formulated to systematically balance the hydraulic conflicts. Therefore, the overarching research objective of this study is to develop a robust surrogate-assisted multi-objective optimization framework capable of decoupling the highly non-linear flow-pressure interactions in large-scale parallel hydraulic test benches. By systematically mapping the physical trade-off boundaries, this research aims to provide a reliable theoretical basis and a flexible engineering decision-making tool to fundamentally resolve the industrial conflict between heat dissipation demands and mechanical seal safety. The specific research objectives of this study are explicitly defined as: (1) minimizing the casing pressure difference ($|P_A - P_B|$) to ensure the mechanical safety of the motor seals; (2) minimizing the total pressure loss ($PL_A + PL_B$) to reduce system energy consumption; and (3) maximizing the pump flow (Q) to guarantee sufficient cooling and flushing capacity during continuous testing. While increasing a greater safety margin, the optimized circuit is also suitable for the subsequent testing of motors with larger displacements, meeting the actual engineering requirements.

The proposed multi-objective framework effectively reconciles the industrial conflict between heat dissipation and mechanical safety, offering a robust, scalable decision-making roadmap for the design and maintenance of large-scale hydraulic test benches.

2. Materials and Methods

2.1 Basic Data

The motor test uses a pair of large-sized inner-curve radial piston hydraulic motors of the Häggblunds CB400400 model. The hydraulic circuit for flushing their casings adopts an Eaton vane pump with a maximum flow rate of 96 L/min. The flushing oil is No. 46 anti-wear hydraulic oil, and its viscosity index can ensure that the viscosity of the motor remains stable under the working condition of 5 - 60 °C, avoiding the increase of casing pressure difference caused by viscosity fluctuation. The circuit is mainly constructed with seamless steel pipes with an inner diameter of 22 mm and a wall thickness of 3 mm, and 90-degree elbows with an inner diameter of 22 mm and a 1.5D (dimension). Five pressure sensors of the Danfoss MBS3250 model are installed at the outlet of the oil pump, the inlets of the two branches, and the casings of the tested motor and the loading motor, and their pressure measurement range is 0 - 600 bar. The connection between the flushing circuit and the motor casing is made by a hose with an inner diameter of 32 mm. The schematic diagram of the structure of this flushing circuit is shown in Figure 1 (b).

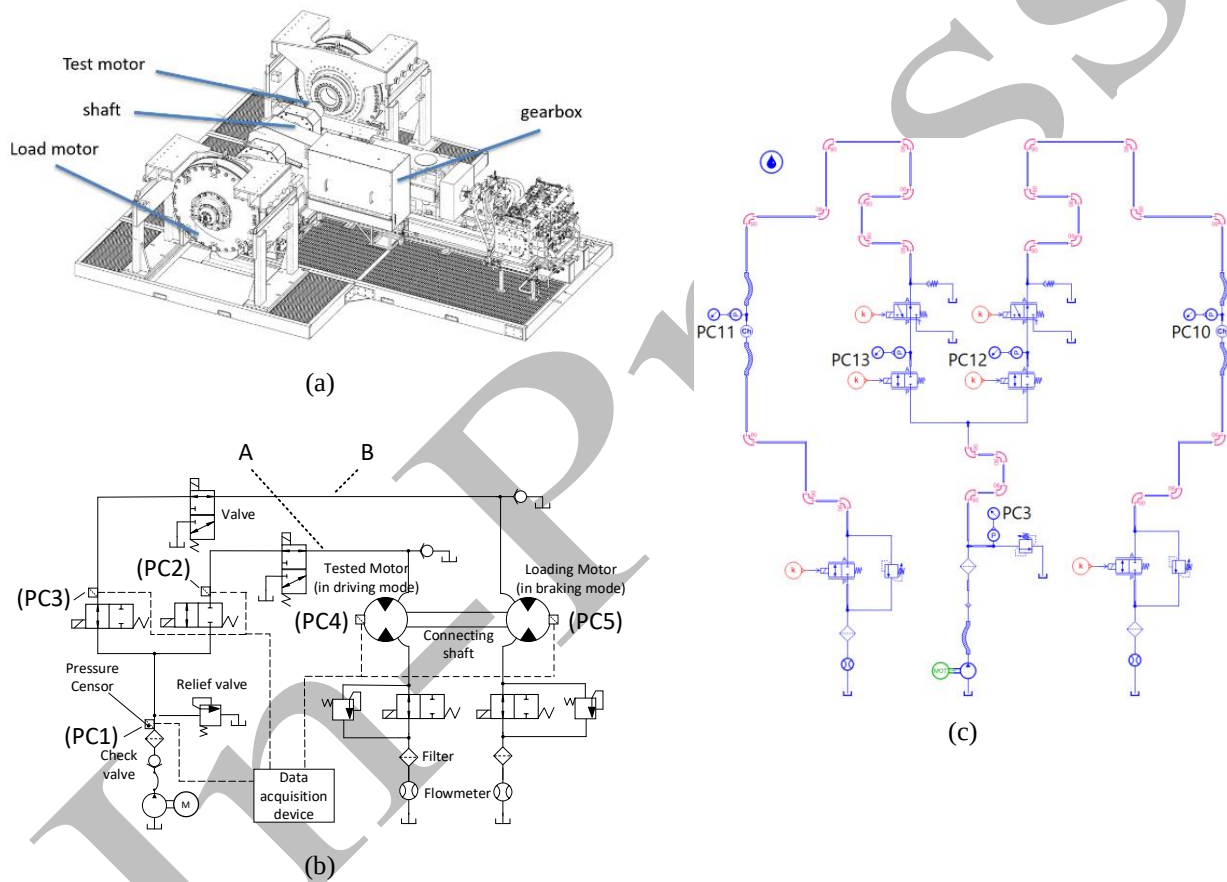


Figure 1. Overview of the parallel hydraulic flushing system and simulation model validation. (a) 3D Schematic diagram of hydraulic motor test bench; (b) Schematic diagram of hydraulic flushing circuit structure; (c) Simulation model of the flushing circuit

2.2 Mathematical Modelling of Pressure Loss and Heat Dissipation

Since the flow of hydraulic oil in pipelines will inevitably cause pressure loss, the value of this pressure loss can be determined by formulas. Among them, the pressure loss of hydraulic oil flowing through a straight pipeline can be calculated using the Darcy-Weisbach formula (1):

$$\Delta p_f = \lambda \frac{l}{d} \frac{\rho v^2}{2} \quad (1)$$

While the local pressure loss occurring at the elbows of the circuit can be calculated using formula (2):

$$\Delta p_r = \zeta \frac{\rho v^2}{2} \quad (2)$$

The total pressure loss is calculated using formula (3):

$$\Delta p = \sum \lambda_i \frac{l_i}{d_i} \frac{\rho v_i^2}{2} + \sum \zeta_i \frac{\rho v_i^2}{2} \quad (3)$$

In the formula, l represents the pipeline length; d denotes the pipeline inner diameter; λ stands for the frictional resistance coefficient; ζ is the local resistance coefficient; v indicates the average flow velocity of the liquid inside the pipeline; ρ represents the fluid density.

Since removing the heat generated by the motor during testing is one of the main purposes of the flushing circuit, the heat in the motor casing originates from the total power loss of the motor, which is expressed by the following formulas:

$$P_m = C \cdot P_o \quad (4)$$

$$P_t = P_m + P_v \quad (5)$$

In the formula (4) and formula (5), C denotes the mechanical loss coefficient, P_o is motor output power, P_m represents the mechanical loss power. P_t stands for the total loss power, and P_v is volume loss power.

For the tested motor, the calculation of its case flushing flow rate is determined by formula (6):

$$q_f = 3.4(P_t - P_a) \quad (6)$$

In formula (6), q_f represents the flushing flow rate of one motor case and P_a denotes the natural heat dissipation power of the motor case to the air.

From these basic equations, it can be concluded that the main causes of pressure loss in the hydraulic circuit are the length of the pipelines and the number of elbows. Moreover, according to the flow rate calculation formula, the flow rate required by the motor during testing can be determined. Therefore, the target parameters for optimizing this hydraulic system can be obtained.

2.3 Model Establishment and Experimental Validation

2.3.1 Collection of test parameters

The pressure difference between the inlet and outlet of the tested motor was set to 150 bar, and the rotational speed was set to 25 r/min. After the loading test had been running for a period of time, the flushing oil pump started automatically and adjusted the flushing flow rate according to the temperature sensor at the motor casing. Once the experiment had stabilized for 30 seconds, pressure data from the pressure sensors at various positions were collected. A set of data was collected every 2 seconds, and this process was repeated three times; the average value of these three sets of data was calculated to form one group of experimental data. This procedure of waiting for stabilization and averaging multiple independent trials was strictly implemented to filter out random fluctuations and ensure experimental repeatability. Furthermore, due to the industrial scale of the test bench, the overall measurement uncertainty is predominantly determined by the inherent accuracy of the calibrated instruments (Type B uncertainty). The technical specifications and maximum uncertainties of the key measurement instruments utilized in the circuit are detailed in Table 1. Given that the relative errors between the AMESim simulation and experimental results (shown in Section 2.3.3) are largely within the combined uncertainty bounds of these industrial sensors, the robustness of the simulation model is considered validated for subsequent surrogate modeling. A total of 6 groups of experimental data were collected in Table 2.

Table 1. Technical specifications and measurement uncertainty of key instruments

Instrument Type	Model	Measurement Range	Accuracy / Maximum Uncertainty
Pressure Sensor	Danfoss MBS3250	0 – 600 bar	±0.5% Full Scale (FS)
Flowmeter	Industrial Gear Flowmeter	0 – 96 L/min	±0.5% of reading

Table 2. Experimental data of the flushing circuit

Number	PC1/bar	PC2/bar	PC3/bar	PC4/bar	PC5/bar	Pumping Flow (L/min)
1	3.62	2.18	2.04	0.82	0.73	62.78
2	3.71	2.24	2.05	0.79	0.74	62.14
3	3.66	2.20	2.03	0.80	0.73	61.60
4	4.49	2.66	2.44	0.96	0.84	69.77
5	4.51	2.68	2.49	0.95	0.85	69.94
6	4.31	2.56	2.44	0.92	0.84	67.70

2.3.2 Establishing AMESim model

After measurement and data collection, the main parameters of the test bench and the hydraulic oil used are presented in Table 3.

The AMESim software was employed to model and simulate this hydraulic flushing circuit. First, a physical model was constructed sequentially through four modules: Sketch, Submodel, Parameter, and Simulation. The specific steps are as follows:

- (1) In the Sketch mode, components such as the pump, hydraulic motor, filter, directional control valve, and 90° elbows were connected in sequence according to the schematic diagram of the test bench's flushing circuit.
- (2) In the Submodel mode, an appropriate Submodel was selected for each component; then, in the Parameter mode, parameters including the pump flow rate, pipeline inner diameter and length, and elbow curvature radius were defined.
- (3) In the Simulation mode, click "Run" to operate the simulation model.

Since the interior of the motor casing requiring flushing is a closed chamber, the "Simple hydraulic chamber" component was selected as a substitute. In addition, considering the flushing circuit's characteristics of medium-length pipelines and no significant oil fluctuation, the HL0001/2/3 and HRBP0011E Submodels which only account for capacitance and resistance were chosen for all pipelines and elbows. For other hydraulic components, their Submodels were selected and their parameter information was filled in with reference to the technical manuals provided by the manufacturers. The established model is shown in Figure 1 (c).

Table 3. Parameters of the test bench

Parameter	Values
A Pipeline length/m	9.3
B Pipeline length/m	10.5
A Number of elbows	8
B Number of elbows	8
Hydraulic oil density / (kg·m ⁻³)	0.88 × 103
Absolute viscosity / (Pa·s)	0.042
bulk modulus/MPa	1.5 × 103
motor case capacity/cm ³	0.7 × 106

2.3.3 Verification and accuracy analysis of the simulation model

Simulation data were obtained by simulating the six groups of working conditions derived from the tests, and a comparison was made between these simulation data and the motor test data, as shown in Figure 2. The simulation error values were calculated using formula (7).

$$RE = \frac{|V_e - V_s|}{V_e} \cdot 100\% \quad (7)$$

In the equation above, RE represents Relative Error, V_e denotes Experimental Value and V_s is Simulation Value.

From the red-marked parameters of the simulation group with a flow rate of 67.70 L/min in Figure 2, it can be observed that two sets of data have relatively large relative errors (error greater than 4.5%). This is mainly caused by the error of sensor data collection in experimental tests and the inability of the simulation software to fully simulate the complex working conditions of the hydraulic flushing circuit during actual operation. However, the errors between all simulation data and experimental values are within 5%, which is within the acceptable range in engineering practice, so this simulation model can be used for the next optimization work.

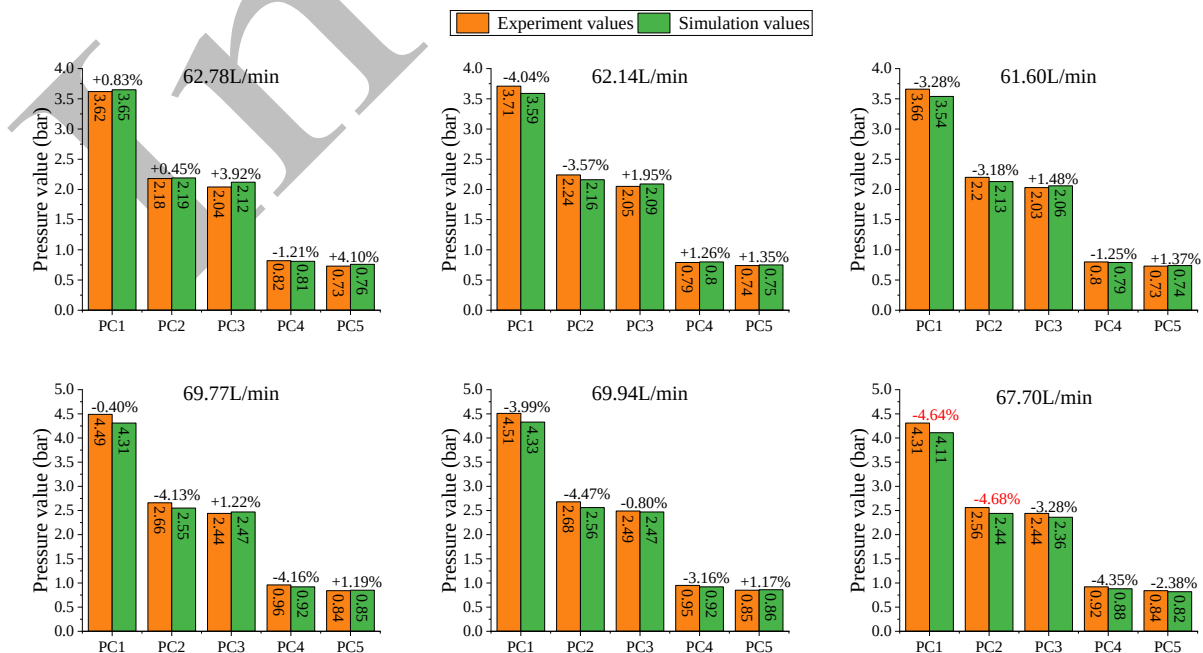


Figure 2. Comparison figure of simulation and test data

2.4 Range of Parameter Values

Given the large number of subsystems within the motor test bench, the hydraulic flushing circuit—one of these subsystems must be routed around other systems during pipeline layout. Excessively long pipelines will increase the frictional pressure loss, while excessively short pipelines will require more elbows for connection, thereby increasing local pressure loss. Therefore, based on the actual conditions of the test bench, the value ranges for the pipeline length and number of elbows were determined for the two parallel flushing circuits: the pipeline for the tested motor (hereinafter referred to as Pipeline A) and the pipeline for the loading motor (hereinafter referred to as Pipeline B). Additionally, the value range for the flushing circuit pump flow rate was calculated using the equations above. These are presented in Table 4, which defines the value boundaries for subsequent hydraulic system optimization.

Table 4. Range of parameters

Parameter	Minimum Values	Maximum Values
Pipeline A length/m	6.5	9.5
Pipeline B length/m	9	12
A Number of elbows	4	8
B Number of elbows	6	9
Pump flow / (L/min)	60	70

3. Results and Discussion

3.1 Experimental Design

After determining the optimal design variables, a multi-objective optimization model for this flushing circuit was established, and its mathematical model is as formula (8):

$$\text{Minimise: } \{f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)\} \quad (8)$$

In the mathematical model:

$$f_1(x) = f_{p1}(x) \quad (9)$$

$$f_2(x) = f_{p2}(x) \quad (10)$$

$$f_3(x) = |f_{p1}(x) - f_{p2}(x)| \quad (11)$$

$$f_4(x) = f_{pL1}(x) + f_{pL2}(x) \quad (12)$$

$$f_5(x) = -Q \quad (13)$$

$$x = [L_A, L_B, EL_A, EL_B, Q]^T \quad (14)$$

In the equations, L_A, L_B, EL_A, EL_B, Q respectively represents the length of Pipeline A, the length of Pipeline B, the number of elbows in Pipeline A, the number of elbows in Pipeline B, and the pump flow rate; $f_1(x), f_2(x), f_3(x), f_4(x), f_5(x)$ denotes the optimization objectives, among them: $f_3(x)$ stands for the pressure difference between the casings of motor A and motor B; $f_4(x)$ is the sum of pressure losses in Pipeline A and Pipeline B; $f_5(x)$ represents the objective of maximizing flow and it takes the negative value here. $f_{p1}(x), f_{p2}(x), f_{pL1}(x), f_{pL2}(x)$ respectively represents the surrogate models: motor casing pressure value at side A, motor casing pressure value at side B, pressure loss of pipeline A and pressure loss of pipeline B. The complete research method flowchart of this study is shown in Figure 3.

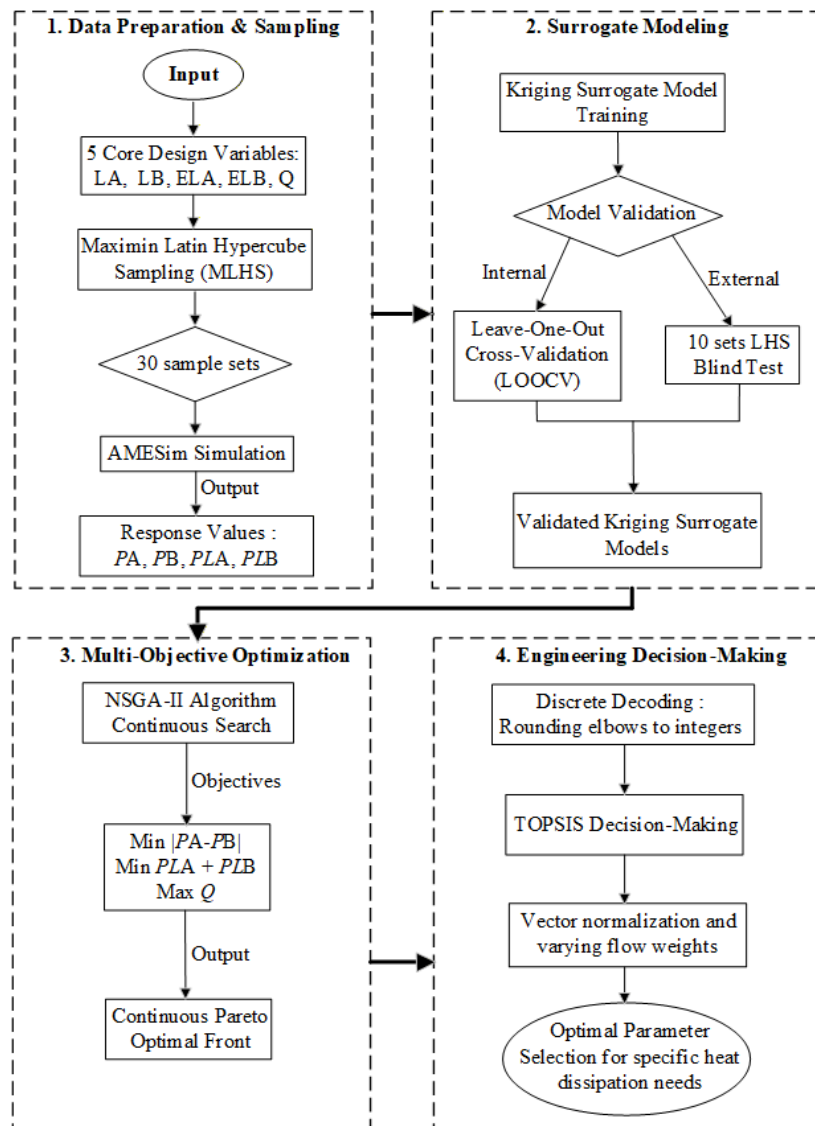


Figure 3. Unified flowchart of the proposed multi-objective optimization framework

3.2 Maximin Latin Hypercube Sampling

The research object of this paper is a 5-dimensional mixed-variable model. To achieve uniform coverage of all operating conditions in its parameter space while minimizing the workload of simulation sampling, Maximin Latin Hypercube Sampling (MLHS) is adopted to obtain experimental samples. Latin Hypercube Sampling (LHS) is a computer-aided experimental design method based on stratified sampling [32], whose core principle is to evenly divide the value range of each design variable into n non-overlapping subintervals (where n denotes the sample size), randomly select 1 sample point within each subinterval, and then randomly pair the sampling values of each variable to form n groups of parameter combinations, ensuring that the full value range of each variable is covered. Aiming at the problem that the basic LHS is prone to sample aggregation and difficult to cover blind areas in high-dimensional space, this paper introduces the Maximin criterion to optimize the sampling results: through iterative adjustment of sample pairing combinations, the minimum Euclidean distance between all sample points is maximized, so that the sample points are uniformly distributed in the 5-dimensional space, avoiding sample aggregation and achieving blind-area-free coverage of operating conditions for multi-variable combinations. Since the number of design variables in this paper is 5, according to relevant criteria in the field of engineering optimization, the sampling size n needs to be greater than or equal to 5 times the number of design variables, and $n=30$ is taken here. After 30 groups of sampling samples are obtained by the above method in MATLAB, they are substituted into the validated AMESim simulation model for numerical analysis of each combination, and the response values of the corresponding optimization objectives are obtained as shown in the Table 5.

Table 5. Sampling values and corresponding response values

	Sampling Values					Response Values			
	LA/m	LB/m	ELA	ELB	Q(L/min)	P1/bar	P2/bar	PL1/bar	PL2/bar
1	8.475	10.510	5	7	64.301	0.8402	0.7636	1.2181	1.3047
2	8.561	9.849	8	7	67.802	0.8973	0.8133	1.3451	1.4092
3	9.272	10.189	5	7	68.174	0.8902	0.8181	1.3629	1.4357

4	8.734	11.895	7	8	60.589	0.7998	0.7121	1.1254	1.2279
5	7.768	10.467	7	7	65.660	0.8713	0.7802	1.2488	1.3465
6	8.025	10.908	8	8	66.211	0.8799	0.7870	1.2836	1.3863
7	7.689	10.005	7	9	62.127	0.8197	0.7342	1.1310	1.2208
8	7.122	11.916	6	7	69.890	0.9407	0.8294	1.3777	1.5362
9	7.441	10.884	6	8	61.898	0.8200	0.7279	1.1182	1.2320
10	6.616	9.558	7	8	60.083	0.7918	0.7061	1.0333	1.1306
11	8.357	9.175	5	9	63.080	0.8294	0.7504	1.1674	1.2310
12	7.038	11.579	4	7	65.760	0.8802	0.7748	1.2251	1.3747
13	7.845	11.632	8	8	61.300	0.8117	0.7199	1.1239	1.2384
14	9.302	10.651	6	6	62.495	0.8210	0.7427	1.1881	1.3516
15	6.524	9.068	5	9	64.481	0.8554	0.7636	1.1559	1.2603
16	6.746	9.790	5	6	68.418	0.9132	0.8152	1.2931	1.4067
17	7.283	11.146	7	8	66.366	0.8859	0.7856	1.2631	1.3920
18	9.110	11.465	5	9	60.877	0.8026	0.7171	1.1358	1.2298
19	8.979	10.361	7	7	61.524	0.8159	0.7356	1.1631	1.2920
20	6.835	10.269	5	7	63.422	0.8421	0.7478	1.1387	1.2555
21	9.406	9.961	7	7	67.446	0.8901	0.8104	1.3562	1.4059
22	8.678	9.344	4	8	65.147	0.8588	0.7780	1.2402	1.3027
23	7.977	9.299	6	8	62.883	0.8273	0.7471	1.1537	1.2225
24	9.015	11.715	6	6	64.935	0.8607	0.7707	1.2675	1.3640
25	8.817	11.208	5	9	67.272	0.8955	0.8008	1.3350	1.4405
26	7.565	9.445	8	8	63.973	0.8441	0.7605	1.1850	1.2618
27	8.273	9.673	7	6	68.973	0.9148	0.8285	1.3693	1.4372
28	8.187	10.701	6	8	69.385	0.9260	0.8293	1.3867	1.4921
29	7.301	11.062	4	7	69.205	0.9280	0.8226	1.3443	1.4830
30	6.916	11.331	5	6	66.98	0.8967	0.792	1.2626	1.4059

3.3 Establishment of The Kriging Model

To support the massive iterative calculations required for subsequent multi-objective optimization, a Kriging surrogate model is adopted to construct the nonlinear mapping relationship between the design variables and the optimization objectives. The Kriging model is a surrogate model based on best linear unbiased estimation, which is specifically designed for computer experiments. Its response relationship is formed by the superposition of a global trend term and a stationary Gaussian stochastic process term, enabling high-precision fitting of black-box systems while outputting uncertainty quantification metrics for the prediction results. In this paper, independent Kriging surrogate models are constructed for the motor casing pressure value at side A, the motor casing pressure value at side B, the motor casing pressure differential and the total circuit pressure loss, respectively: the 5-dimensional design variables are input through MATLAB software, with 30 groups of MLHS samples and their corresponding AMESim response values used as the training dataset; the Gaussian squared exponential kernel, which is universally applied in the engineering field, is selected as the kernel function, and the optimal hyperparameters of the model are solved via the maximum likelihood estimation method to complete the model training.

To verify the accuracy and validity of the established surrogate models, the leave-one-out cross-validation (LOOCV) method is adopted in this paper. The operating principle of LOOCV is as follows: one group is reserved from the 30 samples as the test set each time, and the remaining 29 groups are used as the training set; a Kriging model is trained with the 29 groups each time to predict the response value of the reserved 1 group of samples; after 30 cycles, cross-validation prediction values for all 30 groups of samples are obtained. These cross-validation prediction values are compared with the real values from the AMESim simulation, and the coefficient of determination R^2 , Maximum Relative Error (MRE) and Mean Absolute Error (MAE) are calculated to assess the internal fitting accuracy of the models. However, while LOOCV provides a reliable measure of internal consistency, relying solely on these internal metrics is insufficient to fully establish the external generalization capability of the models in a highly non-linear space. Therefore, an additional rigorous validation utilizing completely unseen test data has been introduced, as detailed subsequently in Section 3.3.1. The parity plots obtained from the validation are shown in the Figure 4. Among them, the coefficients of determination R^2 of the surrogate models for motor casing pressure differential and total circuit pressure loss are 0.9904, 0.9986, 0.9988 and 0.9804, respectively; the maximum relative errors are 1.35%, 0.76%, 1.09% and 2.67%, respectively; the Mean Absolute Errors (MAE) are 0.0027 bar, 0.0006 bar, 0.0021 bar and 0.0096 bar, respectively. All LOOCV validation samples in the plots are closely and uniformly distributed on both sides of the $y=x$ reference line without systematic deviation, which verifies the prediction stability of the models in the full design space.

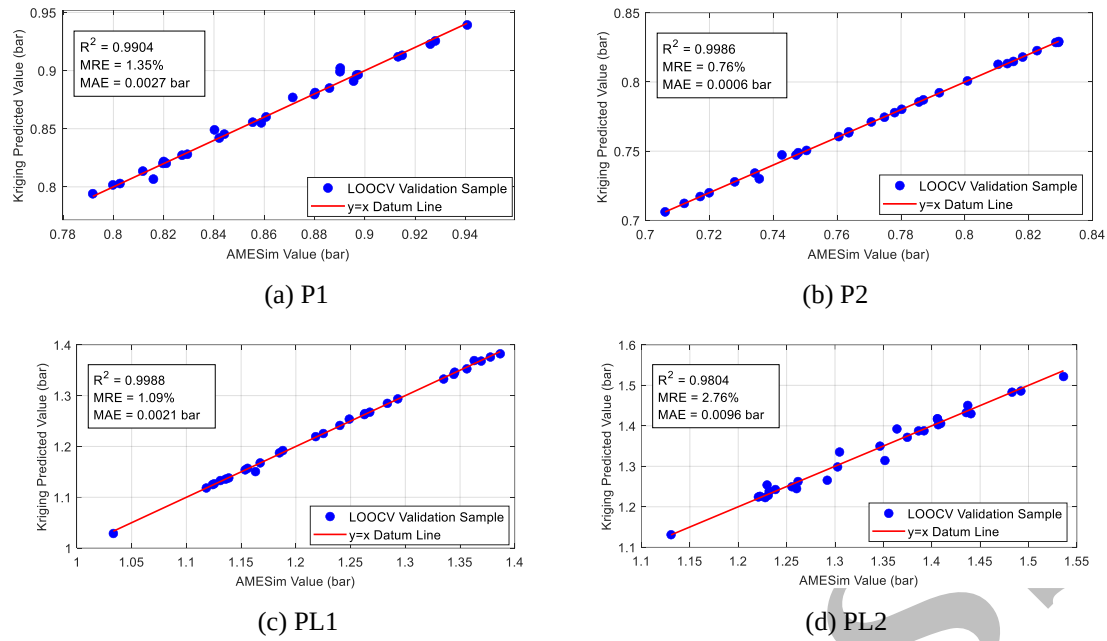


Figure 4. Cross-validation results plots

3.3.1 Justification of sample adequacy and external validation

While the internal LOOCV metrics demonstrate high fitting accuracy, relying solely on 30 MLHS samples for a 5-dimensional space raises theoretical concerns regarding potential overfitting and uncaptured non-linear interactions. To rigorously justify the adequacy of the sample size and evaluate the true generalization capability of the Kriging models, an external blind test was conducted.

An independent test set comprising 10 unseen sample configurations was generated using the Standard Latin Hypercube Sampling (LHS) method. These configurations were simulated in AMESim to obtain the ground truth, which was then compared against the predictions of the established Kriging models. The validation results revealed that the Maximum Relative Error (MRE) for the motor casing pressures was constrained below 1.2%, and the MRE for the total pressure losses was strictly below 5.2%. Such consistently low prediction errors on completely unseen, randomized LHS configurations explicitly demonstrate that the models have accurately captured the underlying physical fluid dynamics without overfitting. Consequently, it is confirmed that the 30 MLHS samples comprehensively covered the feasible design space, proving the sample size to be computationally efficient and fundamentally adequate for this specific parallel circuit optimization.

3.4 Multi-Objective Optimization Algorithm

The core of the multi-objective algorithm NSGA-II (Non-dominated Sorting Genetic Algorithm II) lies in simulating the biological evolution process to search for the Pareto optimal solution set among "multiple conflicting optimization objectives". The Pareto optimal solution set refers to a collection of solutions where improving one objective will inevitably impair at least one other objective. Specifically, NSGA-II evolves a randomly generated initial population into an offspring population with a larger scale through dominance sorting, selection, crossover, and mutation. Subsequently, fast non-dominated sorting is performed to form a new parent population. Finally, the offspring population generated by genetic algorithms is combined with the parent population to form a new population. This algorithm repeats the above steps continuously until the set conditions are met, and its process is shown in Figure 5.

It can be concluded from the mathematical formulas listed earlier that although an increase in flow rate can optimize the heat dissipation efficiency of the motor casing, it will also lead to an increase in pressure loss. Moreover, since Pipelines A and B are in a parallel relationship, changing the parameters of one pipeline will affect the other. Therefore, the research object in this study meets the condition of searching for the optimal solution among "multiple conflicting optimization objectives".

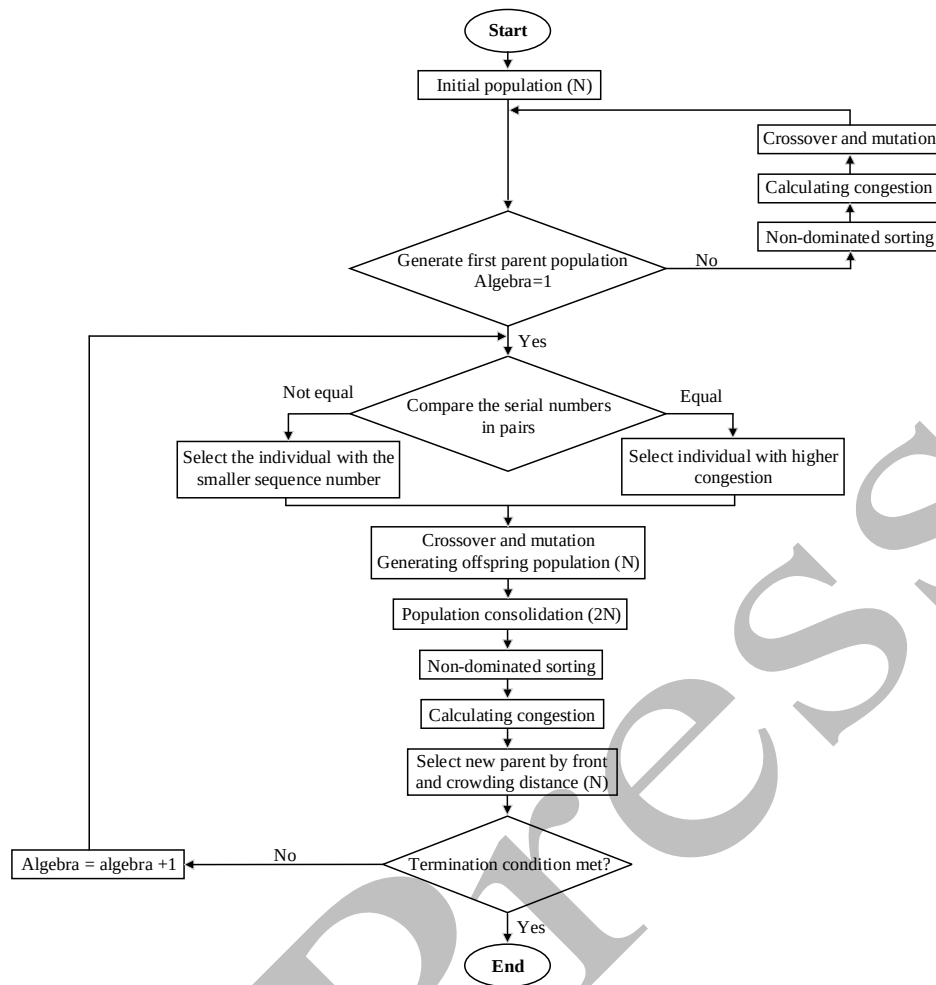


Figure 5. The process of multi-objective optimization algorithm

To balance the continuous search mechanism of the NSGA-II algorithm with the discrete nature of industrial piping components, a 'continuous search, discrete decoding' strategy was implemented in this study. During the algorithmic iteration phase, the integer constraints on the number of elbows (ELA , ELB) were deliberately relaxed, treating them as continuous variables. This relaxation is crucial; enforcing strict integer constraints during the genetic algorithm's evolutionary process would cause the Pareto front to collapse into disconnected discrete layers, severely impairing the algorithm's ability to maintain population diversity and fully explore the highly non-linear fluid dynamics space. Subsequently, during the final engineering decision-making phase, a 'rounding to the nearest integer' mathematical constraint was applied to these variables before the TOPSIS evaluation. This ensures that the finalized parameters rigorously conform to available standardized industrial components.

3.5 Optimization Results

After the Kriging models are successfully validated, the NSGA-II algorithm is executed using MATLAB software. Instead of arbitrary selection, the algorithm hyperparameters are configured based on established literature benchmarks in surrogate-assisted hydraulic optimization [27]-[28] to ensure a strict balance between convergence speed and population diversity. Specifically, the parameters for obtaining the optimal solution set are determined as follows: the population size is 200, the maximum number of iterations is 400, the crossover probability is 0.8, the mutation probability is 0.2, and the elite retention ratio is 0.1. The optimization weights of the five optimization objectives in formula (8) are set to 0.200, 0.200, 0.200, 0.200 and 0.200, respectively. The corresponding three-dimensional plot of the Pareto front is shown in the Figure 6. It can be seen from the plot that the Pareto solution set covers the feasible region of the objective space, and the two-dimensional projection plot of the Pareto optimal solution set shown in the Figure 7 clearly reflects the trade-off relationship among the three conflicting objectives: the pressure differential and total pressure loss increase synchronously with the rise of pump flow rate, which is consistent with the actual engineering law.

To objectively evaluate and select the final engineering parameters from the Pareto optimal set, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was employed. First, to eliminate dimensional discrepancies among the three physical objectives (pressure difference, pressure loss, and flow rate), the objective matrix was standardized using the vector normalization technique. Subsequently, the normalized matrix was multiplied by specific weight vectors. The weight assignment rationale was strictly driven by practical testing constraints: to maintain baseline system safety, the relative weights for pressure difference and pressure loss were kept equal; meanwhile, the weight for

the pump flow was dynamically adjusted (as listed in Table 6) to accommodate the varying heat dissipation demands of different tested motors. Finally, the Euclidean distance metric was utilized to calculate the distance of each candidate solution from the positive ideal solution (D^+) and the negative ideal solution (D^-). The solutions were ultimately ranked based on their relative closeness coefficient, calculated as $C = \frac{D^-}{D^+ + D^-}$, allowing engineers to pinpoint the optimal parameter combinations for specific thermal load conditions. It should be noted that while the TOPSIS evaluation yields mathematically exact values for pipeline lengths (e.g., 9.49 m), real-world implementation is inherently subject to engineering constraints. Standardized manufacturing dimensions for seamless steel pipes, the discrete availability of industrial elbows, and inevitable on-site installation tolerances dictate that these algorithmic outputs serve as guiding baselines rather than rigid specifications. In practice, engineers must map these theoretical optima to the nearest commercially available standard components. This physical deviation further underscores the necessity of obtaining a uniformly distributed Pareto front, as it provides a robust spectrum of alternative near-optimal solutions when exact parameter adoption is practically constrained.

Additionally, in Table 5, there are three sets of parameter combinations that are identical. This phenomenon arises because the Pareto optimal solution set converges to the same parameter combination within this flow rate interval, which belongs to the optimization plateau period in the iterative solution process. By setting different weights for the flow rate, the algorithm can derive the optimal solution of the parameter combination under corresponding working conditions: in practical engineering, for low-load test scenarios or the testing of low-power hydraulic motors, the parameter combination with a smaller flow weight can be selected to achieve energy consumption saving; for high-load test scenarios or the testing of higher-power hydraulic motors, the parameter combination with a larger flow weight can be selected to better remove the impurities and heat generated in the motor casing during the test.

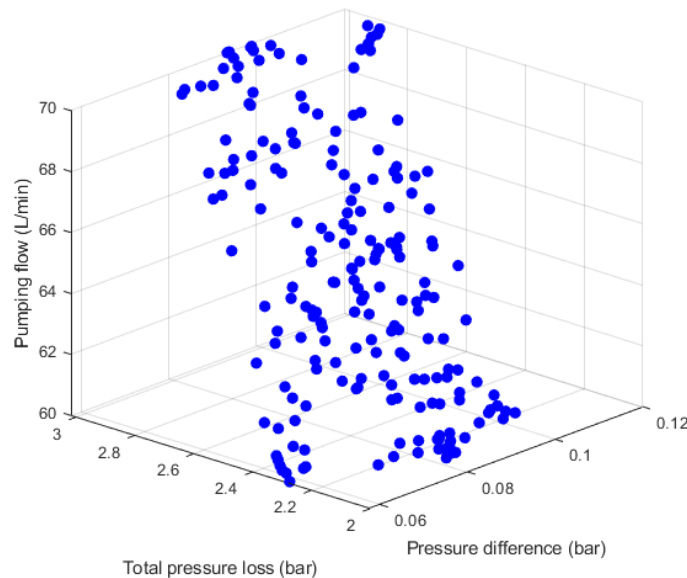


Figure 6. Three-dimensional plot of the Pareto front

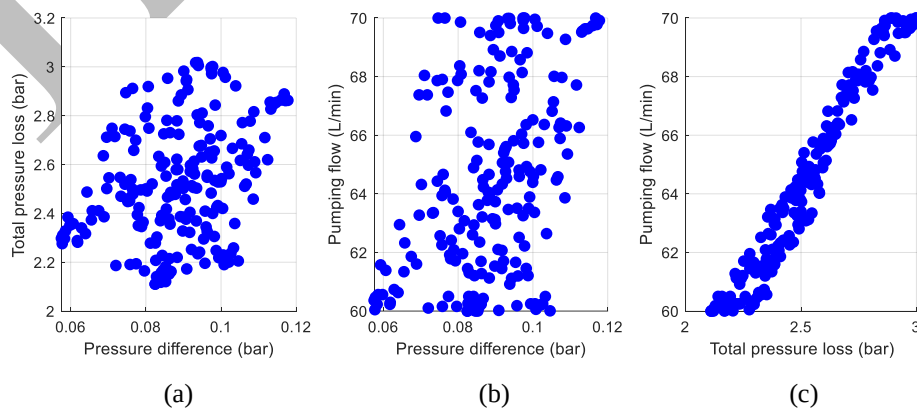


Figure 7. Two-dimensional projection plot of the Pareto optimal solution

The Pareto optimal solutions presented above reveal a strict physical trade-off inherent to the parallel hydraulic circuit. From a fluid dynamics perspective, increasing the pumping flow enhances the heat dissipation and debris flushing

capacity within the motor casings. However, higher flow velocities exponentially increase fluid friction against the pipe walls (on-way resistance) and exacerbate localized flow separation at the elbows (local resistance), causing the inevitable surge in total pressure loss. Furthermore, due to the asymmetric geometric layout of the two parallel branches (variances in pipe lengths and elbow quantities), increasing the total flow disproportionately amplifies the dynamic pressure drops between Pipeline A and B. This fluid kinetic divergence directly induces the casing pressure difference. Therefore, the Pareto front essentially represents the physical and engineering contradiction between maximizing the system's cooling capability and protecting the vulnerable motor shaft seals from excessive asymmetric pressure loads.

Table 6. Optimal solution sets under different flow weights

Parameters Values						Objective Values			
Flow weights	LA /m	LB /m	ELA	ELB	Q (L/min)	Case A pressure /bar	Case B pressure /bar	Pressure differential/bar	Total pressure loss/bar
0.200	9.50	9.04	5	7	60.05	0.7779	0.7201	0.0578	2.2760
0.225	9.49	9.04	5	7	60.36	0.7823	0.7248	0.0575	2.2977
0.250	9.38	9.05	5	7	61.58	0.7997	0.7404	0.0593	2.3844
0.275	9.38	9.05	5	7	61.58	0.7997	0.7404	0.0593	2.3844
0.300	9.49	9.04	5	7	67.38	0.8812	0.8116	0.0696	2.7117
0.325	9.38	9.04	5	7	68.04	0.8911	0.8201	0.0710	2.7483
0.350	9.38	9.04	5	7	68.04	0.8911	0.8201	0.0710	2.7483
0.375	9.48	9.00	5	8	70.00	0.9206	0.8459	0.0747	2.8941
0.400	9.48	9.00	5	8	70.00	0.9206	0.8459	0.0747	2.8941

3.5.1 Comparative analysis of optimization algorithms

To rigorously justify the selection of the NSGA-II algorithm over other heuristic methods, a comparative analysis was conducted using a Multi-Objective Pattern Search (MOPS) algorithm as an alternative benchmark. Both optimization processes were driven by the exact same validated Kriging surrogate models under comparable evaluation budgets. As depicted in Figure 8, a clear distinction in solution diversity is observed. The alternative MOPS algorithm (marked by red crosses) successfully approached the optimal trade-off surface but suffered from significant local clustering, failing to explore the full extent of the optimal front and leaving obvious coverage gaps. Conversely, the NSGA-II algorithm (marked by blue solid circles) demonstrated superior population diversity, yielding a uniformly distributed and expansive Pareto optimal set. This robust and continuous spread of non-dominated solutions is a direct consequence of NSGA-II's crowding distance operator, which effectively prevents premature convergence to a narrow region. For the parallel hydraulic flushing circuit, obtaining such a diverse and uniform Pareto front is essential, as it provides a comprehensive and un-biased spectrum of design alternatives for the subsequent TOPSIS evaluation.

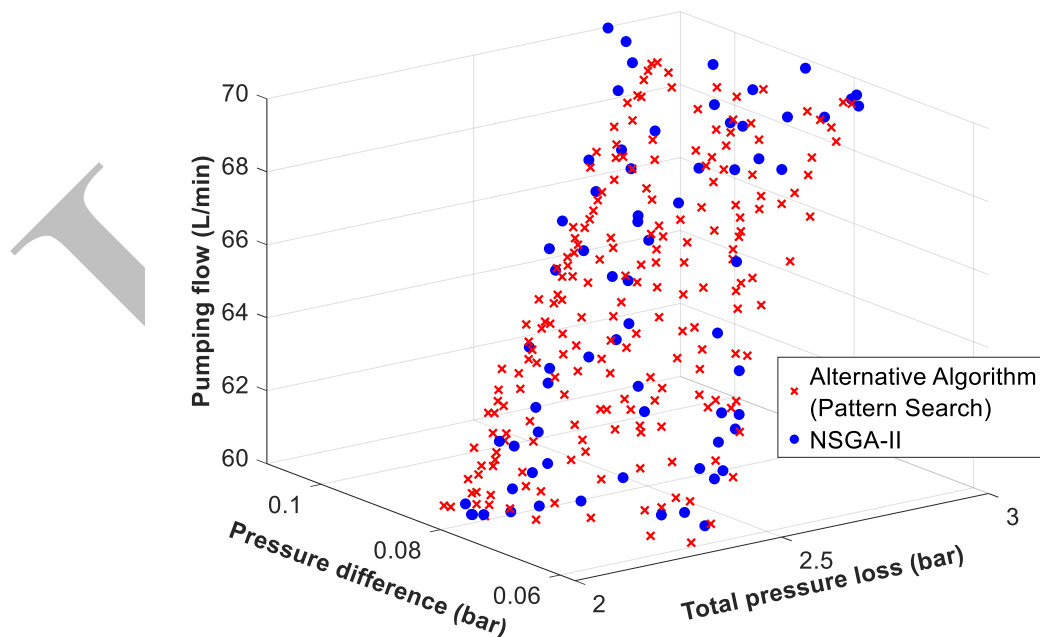


Figure 8. Comparison of Pareto fronts: NSGA-II vs. Alternative algorithm

3.6 Comparison Before and After Optimization

The flow value from the optimized design combination with a flow weight of 0.2 is substituted into the pre-optimization AMESim model for calculation, and the corresponding values obtained are compared with the optimized solution

combination, as shown in the Table 7. By comparing the values before and after optimization, it can be concluded that: after optimization, the casing pressures of the two motors on Side A and Side B of the flushing circuit are reduced from 0.7954 bar and 0.7311 bar to 0.7779 bar and 0.7201 bar, which are reduced by 2.2% and 1.5% compared with those before optimization, respectively; the pressure differential between the two motor casings is reduced from 0.0643 bar to 0.0578 bar, which is reduced by 10.1% compared with the unoptimized state; the total pressure loss is reduced from 2.2943 bar to 2.276 bar, which is reduced by 0.8% compared with the unoptimized state. While the 0.8% reduction in total pressure loss appears marginal in terms of energy savings, the primary engineering significance of this optimization lies in equipment safety. Notably, the casing pressure differential was reduced by 10.1% (from 0.0643 bar to 0.0578 bar). Given that the shaft seals of such large-scale motors are highly vulnerable to asymmetric pressure loads (with a tolerance typically below 3 bar), this 10.1% improvement is critical. It effectively minimizes eccentric wear on the seals during weeks of continuous testing. Therefore, the enhanced operational reliability far outweighs the computational costs introduced by the optimization framework. To quantitatively contextualize these optimization margins, recent benchmark studies on simpler or isolated hydraulic networks [27] report single-objective pressure loss reductions of approximately 9.0%. While the 0.8% pressure loss reduction achieved in this study appears numerically smaller than such benchmarks, it represents a strictly constrained optimum within a strongly coupled multi-objective framework. In this parallel flushing circuit, attempting to force a 9% reduction in pressure loss would necessitate an unacceptable drop in the cooling flow rate or trigger a severe spike in the casing pressure differential, immediately leading to thermal or mechanical failure. Therefore, securing a dominant 10.1% improvement in the critical mechanical safety metric (pressure differential) while simultaneously maintaining a net-positive reduction in total pressure loss demonstrates the superior practical effectiveness of this framework compared to traditional single-objective benchmarks.

Beyond the numerical improvements, this study offers significant theoretical and practical advancements. Theoretically, we proposed a ‘continuous search, discrete decoding’ strategy that resolves the inherent conflict between algorithmic continuity and the discrete nature of industrial components, providing a robust mathematical template for optimization in complex parallel hydraulic architectures. Practically, the established surrogate-assisted framework offers a validated, computationally efficient roadmap for the design and maintenance of large-scale motor test benches. By quantitatively revealing the physical trade-off boundaries between heat dissipation and mechanical safety, this work enables engineers to systematically enhance equipment reliability and adapt to diverse testing loads through flexible decision-making, transcending the limitations of traditional empirical design methods.

Table 7. Parameter comparison before and after optimization

	Parameter	Pre-optimization	Post-optimization	Reduction rate
Parameters values	Pipeline A length/m	9.3	9.5	
	Pipeline B length/m	10.5	9.04	
	A Number of elbows	8	5	
	B Number of elbows	8	7	
Objective values	Case A pressure/bar	0.7954	0.7779	2.2%
	Case B pressure/bar	0.7311	0.7201	1.5%
	Pressure differential/bar	0.0643	0.0578	10.1%
	Total pressure loss/bar	2.2943	2.2760	0.8%

4. Conclusions

Aiming at the strong physical conflicts between flushing flow, casing pressure, and pipeline pressure loss in parallel hydraulic circuits, this study established a surrogate-assisted multi-objective optimization framework. By integrating Maximin Latin Hypercube Sampling (MLHS), high-precision Kriging models, and the NSGA-II algorithm, the complex non-linear interactions within the large-scale motor test bench were effectively decoupled. The systematic integration of these methods enabled a comprehensive exploration of the design space while maintaining high computational efficiency.

The optimization results directly resolve the initially stated engineering contradictions. Under the balanced TOPSIS decision-making, the casing pressure differential—the most critical metric for motor seal safety—was reduced by 10.1%, while the total circuit pressure loss was simultaneously decreased by 0.8% without compromising the required flushing flow rate. These quantitative improvements demonstrate that the proposed framework effectively reconciles the conflicting demands of heat dissipation, energy efficiency, and mechanical reliability. This study provides a robust technical roadmap and a validated decision-making tool for the multi-objective optimization of complex parallel hydraulic systems.

Finally, several limitations of this study should be acknowledged. First, the current optimization is based on static simulation models and does not account for transient thermal-fluid fluctuations or pipe vibrations during rapid pressure shifts. Second, while the MLHS-Kriging framework is robust, the training dataset is specific to the Hägglunds CB400 motor test bench; thus, generalizing the results to significantly different hydraulic architectures would require supplementary sampling. Future research will focus on integrating dynamic fluid-structure interactions and developing a more universal surrogate model for diverse parallel hydraulic systems.

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Declaration of Competing Interests

The author declares no conflicts of interest.

CRediT Author Contribution Statement

Yan Cao (Conceptualization; Methodology; Software; Data curation; Writing - original draft; Visualization)

Bing Zhang (Validation; Investigation; Resources; Data curation)

Jingding Tian (Software; Formal analysis; Validation)

Jiawei Wu (Software; Formal analysis; Writing - review and editing)

Hongyu Lu (Investigation; Writing - review and editing)

Hao Chen* (Conceptualization; Writing - review & editing; Supervision; Project administration)

Availability of Data and Materials

The data supporting this study's findings are available on request from the corresponding author.

Ethics Statement

This study did not involve human participants or animals. Ethical approval was therefore not required.

Generative Artificial Intelligence Disclosure

The authors claim that artificially intelligent-assisted technologies, such as generative AI, were not used to generate content, ideas, or theories. We have just utilised AI to enhance readability and refine the language. This was used with extreme human control and oversight. The authors take full responsibility for reviewing and approving the content.

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