Su et al.
Chinese Journal of Mechanical Engineering (2024) 37:38
https://doi.org/10.1186/s10033-024-01022-8

Chinese Journal of Mechanical Engineering

ORIGINAL ARTICLE

Open Access

Parameter Estimation of a Valve-Controlled Cylinder System Model Based on Bench Test and Operating Data Fusion

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Abstract

The accurate estimation of parameters is the premise for establishing a high-fidelity simulation model of a valve-controlled cylinder system. Bench test data are easily obtained, but it is challenging to emulate actual loads in the research on parameter estimation of valve-controlled cylinder system. Despite the actual load information contained in the operating data of the control valve, its acquisition remains challenging. This paper proposes a method that fuses bench test and operating data for parameter estimation to address the aforementioned problems. The proposed method is based on Bayesian theory, and its core is a pool fusion of prior information from bench test and operating data. Firstly, a system model is established, and the parameters in the model are analysed. Secondly, the bench and operating data of the system are collected. Then, the model parameters and weight coefficients are estimated using the data fusion method. Finally, the estimated effects of the data fusion method, Bayesian method, and particle swarm optimisation (PSO) algorithm on system model parameters are compared. The research shows that the weight coefficient represents the contribution of different prior information to the parameter estimation result. The effect of parameter estimation based on the data fusion method is better than that of the Bayesian method and the PSO algorithm. Increasing load complexity leads to a decrease in model accuracy, highlighting the crucial role of the data fusion method in parameter estimation studies.

Keywords Valve-controlled cylinder system, Parameter estimation, The Bayesian theory, Data fusion method, Weight coefficients

1 Introduction

A valve-controlled cylinder system is a typical hydraulic drive system consisting of a pilot handle, control valve and cylinder. It is widely used in construction, agriculture, aerospace and other fields, which require low energy consumption, stable control and a fast response. To obtain good valve-controlled cylinder system performance, it is often necessary to optimise the design and verification of system parameters and control algorithms. Due to the cost of a prototype and trial, a simulation model is usually used to replace a prototype to design and verify the optimisation scheme. The accuracy of a simulation model directly affects the effectiveness of the optimisation scheme, and the accurate estimation of parameters is the premise for establishing a high-fidelity valve-controlled cylinder system simulation model.

Valve-controlled cylinder system simulation model parameter estimation requires the support of system data. Parameter estimation research uses the load data as the model input condition to optimise the error between the simulation results and the system tested data. The smaller the error between the two, the more accurate the parameter estimation results. Parameter estimation is a

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simulation model parameter optimisation problem. Yan et al. [1] estimated the model parameters of a valve-controlled cylinder system using the recursive least squares method. Based on this model, the maximum error in predicting the general trajectory tracking speed was 13%. Wang et al. [2] estimated the parameters of a discrete model of a valve-controlled cylinder system using the Particle Swarm Optimization (PSO) algorithm. A comparison with the results obtained using the least squares method demonstrated the parameter estimation capability of the PSO algorithm. Aboelela et al. [3] estimated the parameters of a valve-controlled cylinder system using the Matlab/Simulink parameter identification toolbox, achieving satisfactory identification results. Similarly, Liu et al. [4] estimated the parameters of a hydraulic drive unit using the Matlab/Simulink parameter identification toolbox. Although the integrated error in this study was only 1.51%, the fitting between the simulation and experimental results was moderate. Among these parameter estimation studies, the Matlab/Simulink parameter identification toolbox was found to be the most convenient tool, and the PSO algorithm yielded the best results. Essa et al. [5] also discussed a parameter estimation method for a valve-controlled cylinder system based on a black box state space model. However, black box models lack any internal knowledge of the system. In other studies on parameter estimation of hydraulic systems, Nápoles-Báez et al. [6] estimated the parameters of a hydraulic actuator using the Matlab/Simulink parameter identification toolbox. Lu et al. [7] determined the optimal parameters of a Pump-Motor Servo System (PMSS) PID speed controller based on a hybrid Grey Wolf Optimization (GWO) and Particle Swarm Optimization (PSO) algorithm, achieving constant speed control of the PMSS.

More importantly, data are the benchmark for parameter estimation of a valve-controlled cylinder system model. Only accurate data corresponding to the actual operating conditions can ensure the accuracy of parameter estimation results. The aforementioned research on parameter estimation employed various optimization algorithms, all conducted based on bench tests, making the bench test data the reference for parameter estimation. While bench test data offers the advantage of convenient collection, it falls short in simulating actual operating conditions of the system, leading to a discrepancy between the test data and real operating conditions [8]. Consequently, there is an inherent limitation in benchmarking parameter estimation research solely based on bench test data. Operating data, on the other hand, originates from the actual system operation processes of the system and includes real load conditions and personalized environmental information [9, 10]. Nevertheless, acquiring direct measurements of operating data from control valves poses a complex and formidable challenge. This task entails the installation of various sensors, including flow rate sensors, and the intricate design and arrangement of external piping systems. External piping introduces substantial pressure losses, leading to consequential measurement inaccuracies. Compounding the challenge are limitations in operational space, intricate equipment structures, and adverse working conditions, further complicating the acquisition of precise control valve operating data. Consequently, attaining accurate control valve operating data results necessitates substantial time and financial resources. Existing research on construction machinery operating data does not involve collecting control valve operating data [11, 12]. Feng et al. [13] estimated the model parameters of a valve-controlled cylinder system through cylinder operating data. Since cylinder displacement data are not the direct control valve data, this method causes deviations in control valve parameter estimation. Whether bench test or operating data are used in parameter estimation research, the estimation results accuracy is affected to varying degrees. Suppose a reasonable method can be selected to fuse the two data so the parameter estimation includes both the control valve output data and the actual load information. In that case, the system parameter estimation results will be more accurate.

In studying the model parameter estimation of valve-controlled cylinder systems, model parameter estimates obtained based on bench test or operating data can be regarded as prior information for the final parameter estimates. Research on model parameter estimation using these two sets of prior information meets the requirements of bench test and operating data fusion. If there are multiple priors regarding the parameters to be estimated, a common approach for fusing prior information is to average all the multiple priors [14]. However, the deviations of the different opinions are not well quantified in the averaging approach. Pooling methods such as the linear and geometric pooling methods allow unequal weights for each prior and emphasize the diversity of multiple priors [15–17]. Based on the geometric pooling method, Poole et al. [18] pioneered the incorporation of Bayesian theory to combine distinct prior information, enabling the estimation of system performance parameters. Specifically, Bayesian theory is highly regarded in parameter estimation research because it can update the probability distribution of unknown variables by integrating information from multiple data sources [19, 20]. Yang et al. [21] proposed an adaptive Bayesian method based on geometric pooling for evaluating the performance of products with hierarchical structural characteristics. Yang et al. [22] fused inconsistent prior information using Bayesian theory and geometric pooling methods. The proposed approach shows significant advantages in parameter estimation and reliability assessment. Jia et al. [23] proposed a Bayesian-based multi-level system analysis approach for fusing multi-source data at the lower level, resulting in the posterior distribution of model parameters. As mentioned earlier, combining pooling methods and Bayesian theory has proven to be a reliable approach for system data fusion. Currently, this method is widely used in system reliability estimation. Furthermore, it has also been applied in animal population studies [18, 24], urban simulation [25], climate forecasting [26], and other fields. However, its application in parameter estimation research on valve-controlled cylinder systems has not been reported thus far. Addressing the limitations in the research of model parameter estimation for valve-controlled cylinder systems, as well as leveraging the advantages of data fusion method, we propose a data fusion method based on pooling fusion and Bayesian theory for estimating the parameters of valve-controlled cylinder systems.

In summary, this study aims to fuse bench test and operating data using the pooling method and Bayesian theory to utilize the information from both data fully. This data fusion method will be used to estimate and analyse model parameters for valve-controlled cylinder systems. The remainder of this paper is arranged as follows: Section 2 establishes a simulation model of the valve-controlled cylinder system and analyzes the model parameters; Section 3 introduces the test bench and operating data fusion method; Section 4 data acquisition; Section 5 results and discussion. Section 6 summarises this paper.

2 Valve-Controlled Cylinder System Modelling and Parameter Analysis

The research object of this study is the valve-controlled cylinder system of an excavator boom. It is a typical complex nonlinear system composed of a pilot handle, control valve and cylinder, as shown in Figure 1. During boom lifting, the pilot handle controls the pilot pressure signal P_{XAb} to drive the control valve spool to move and open the valve. The oil flows into the cylinder through the *P*-*A* circuit, drives the cylinder to move, and returns to the tank through the *B*-*T* circuit. Similarly, during the boom lowering process, the pilot pressure signal is P_{XBb}, and the control valve and cylinder move opposite to the lifting process. This research studies the mathematical model of the control valve and cylinder in the system without considering the pilot handle dynamic model.

The dynamic equation of the control valve is as follows:

$$P_{pilot}A_v - F_0 = m_v\frac{d^2x_v}{dt^2} + B_v\frac{dx_v}{dt} + K_vx_v, \tag{1}$$

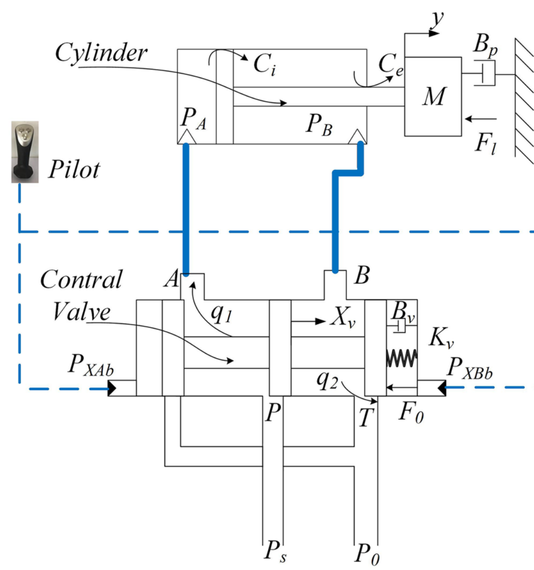


Figure 1 Valve-controlled cylinder system

where P_{pilot} is the pilot pressure, A_v is the valve spool cross-sectional area, F_0 is the external force applied to the control valve. The valve spool is primarily subjected to static pressures, such as spring preload, and the impact of transient fluid dynamics and frictional forces on the control valve was ignored [27]. And m_v is the mass of the valve spool, B_v is the damping coefficient, K_v is the spring stiffness, and x_v is the displacement of the valve spool.

The flow rate equation at the outlet of the control valve is as follows:

$$q_1 = \begin{cases} C_qW\sqrt{2(p_p - p_A)/\rho}, \ x_v > 0, \\ 0, \ x_v = 0, \\ C_qW\sqrt{2(p_A - p_T)/\rho}, \ x_v < 0. \end{cases} \tag{2}$$

The flow rate equation at the inlet of the control valve is as follows:

$$q_2 = \begin{cases} C_qW\sqrt{2(p_B - p_T)/\rho}, \ x_v > 0, \\ 0, \ x_v = 0, \\ C_qW\sqrt{2(p_p - p_B)/\rho}, \ x_v < 0, \end{cases} \tag{3}$$

where C_q is the flow rate coefficient, W is the overflow area, p_p is the main pump outlet pressure, p_T is the tank pressure, p_A is the cylinder large cavity pressure, and p_B is the cylinder small cavity pressure.

The overflow area W is calculated using the area equivalent formula [28], as shown in Figure 2.

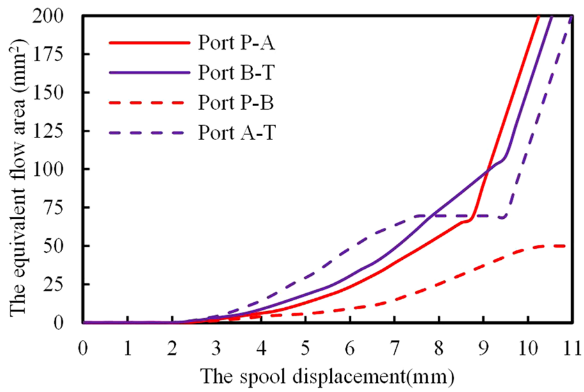


Figure 2 Overflow area of the control valve

Considering the cylinder leakage characteristics and the compressibility of hydraulic oil, the flow rate equation at the cylinder inlet is:

$$\begin{cases} q_1 = A_A \frac{\mathrm{d}y}{\mathrm{d}t} + C_i(p_A - p_B) + C_e p_A + \frac{V_A}{\beta_e}\frac{\mathrm{d}p_A}{\mathrm{d}t}, \\ V_A = V_{A0} + A_A y. \end{cases} \tag{4}$$

The cylinder outlet flow rate equation is

$$\begin{cases} q_2 = A_B \frac{\mathrm{d}y}{\mathrm{d}t} - C_i(p_A - p_B) - C_e p_B - \frac{V_B}{\beta_e}\frac{\mathrm{d}p_B}{\mathrm{d}t}, \\ V_B = V_{B0} - A_B y, \end{cases} \tag{5}$$

where A_A and A_B are the piston areas of cylinder's large and small cavities, y is the displacement of the cylinder, C_i and C_e are the cylinder's internal and external leakage coefficients, respectively, β_e is the equivalent bulk elastic modulus of hydraulic oil, V_{01} and V_{02} are the initial volumes of large and small cavities, and P_A and P_B are the pressures in cylinder's large and small cavities.

The expressions of V_{A0} and V_{B0} are as follows:

$$\begin{cases} V_{A0} = V_{Ad} + A_A L_0, \\ V_{B0} = V_{Bd} + A_B(L - L_0), \end{cases} \tag{6}$$

where V_{Ad} and V_{Bd} are the dead zone volumes of the large and small cavities of the cylinder, respectively, L is the maximum stroke of the cylinder, and L_0 is the initial position of the cylinder.

Based on the load characteristics of the cylinder, the force balance equation of the cylinder is described as follows:

$$A_A p_A - A_B p_B = M\frac{\mathrm{d}y^2}{\mathrm{d}t} + B_p\frac{\mathrm{d}y}{\mathrm{d}t} + Ky + F_f + F_l, \tag{7}$$

where M is the total mass of the cylinder and the load, B_p is the damping coefficient of the cylinder, K is the load stiffness, F_f is the coulomb friction, F_l is the load force. In this paper, the minor friction force F_f relative to the load force F_l is ignored in a valve-controlled cylinder system.

According to Eqs. (1) to (7), a valve-control cylinder system block diagram [29–31] is established, as shown in Figure 3, from which the valve-controlled cylinder system simulation model is established.

In the system model, the control valve parameters include A_v, F_0, m_v, B_v, K_v, C_q,ρ, while q_1 (q_2) represent the control valve output variables, corresponding to the valve spool displacement and flow rate at the valve port, respectively. Parameters in the cylinder include A_A, A_B, C_i, C_e,β_e, V_{Ad}, V_{Bd}, L_0, M, B_p and K. S is the output variable of the cylinder, representing the displacement of the

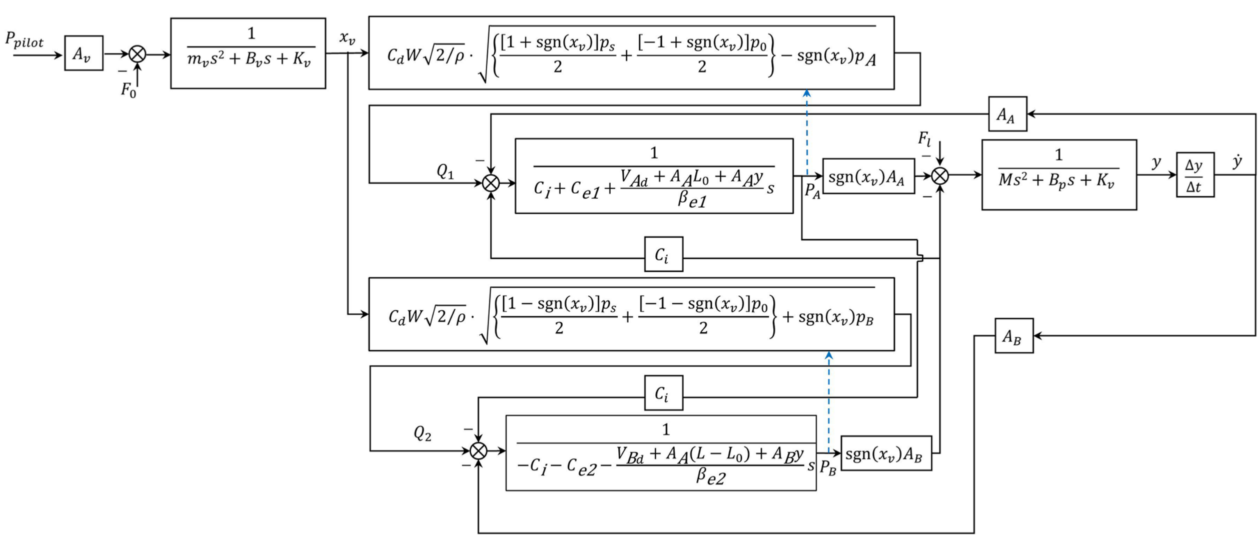


Figure 3 Valve-controlled cylinder system block diagram

Table 1 Parameters of the valve-controlled cylinder system

Parameter	Description	Empirical/measured values	Unit
A_v	The spool cross-sectional area	61.5	mm^2
F_0	External force on spool	300	N
m_v	Spool mass	2	kg
B_v	Damping coefficient	280	N·s/m
K_v	Spring stiffness	120	N/mm
ρ	Hydraulic oil density	850	kg/m^3
P_p	Pump pressure	Measurement data	MPa
P_T	Tank pressure	Measurement data	MPa
C_q	The flow rate coefficient	0.7	–
x_v	Spool displacement	Measurement data	mm
q_1, q_2	Flow rate at the valve port	Measurement data	L/min
A_A, A_B	Piston areas of cylinder's large and small cavities	1.13×10^4, 5.6×10^3	mm^2
p_A, p_B	Pressure of cylinder's large and small cavities	Measurement data	MPa
C_i, C_e	Cylinder internal and external leakage coefficient	365, 320	mm^3/MPa/s
β_e	Hydraulic oil equivalent bulk modulus	855	MPa
V_{Ad}, V_{Bd}	Dead volumes of cylinder large and small cavities	6.65×10^5, 4×10^5	mm^3
L_0	Initial position of cylinder	0.9	m
M	Cylinder and load total mass	2700	kg
B_p	Cylinder damping coefficient	86000	N·s/m
K	Load stiffness	0	N/mm
S	Cylinder displacement	Measurement data	m

cylinder. The description, experience or measured value of each parameter is listed in Table 1.

The empirical values of F_0, B_v, K_v, C_q, C_i, C_e,β_e and B_p in the valve-controlled cylinder system simulation model are inaccurate, so accurate values need to be obtained through parameter estimation research. A_v, A_A, A_B, V_{Ad} and V_{Bd} are measurable design parameters of the component, and L_0 is the initial value of the cylinder, which shall be measured and recorded before each test.

The pump-valve bench test can collect data x_v, q_1 (q_2), p_p and p_A through which the control valve model parameters can be estimated. However, p_p and p_A are simulated loads; the difference between them and the operation conditions causes deviations in the control valve parameter estimation. In addition, the pump-valve bench test cannot collect cylinder data, and the cylinder parameters cannot be estimated through the bench test data. On the other hand, under the operation conditions, x_v and q_1 (q_2) are challenging to collect, and only the cylinder operating data can be used to estimate the parameters in the valve-controlled cylinder system model. Since the cylinder operating data are indirect control valve data, this leads to a deviation in the control valve parameter estimation.

Whether bench test or operating data are used, a deviation in parameter estimation results will occur. Consider the fusion of the two parameter estimation results to make the parameter estimation include both actual load data and control valve data. A comparison between the three methods is shown in Figure 4.

3 Parameter Estimation Method Based on Bench Test and Operating Data Fusion

The proposed data fusion method in this study is based on the pooling method and Bayesian theory. For the continuous parameter vector $\boldsymbol{\theta}$, the posterior supported by the system tested data D can be expressed by the Bayesian formula as follows [32–34]:

$$p(\boldsymbol{\theta}|D) = \frac{p(D|\boldsymbol{\theta})p(\boldsymbol{\theta})}{p(D)} \tag{8}$$

where $p(\theta)$ is the prior probability distribution of the parameter vector $\boldsymbol{\theta}$, $p(D|\boldsymbol{\theta})$ is the joint probability density of the parameter vector $\boldsymbol{\theta}$ and the system tested data D, and $p(D) = \int p(\mathrm{D}|\theta)p(\theta)\mathrm{d}\theta$ is the normalisation constant. When a simulation model is a group of parameter vectors $\boldsymbol{\theta}^*$, the relationship between the system tested data and the simulation results is:

$$T_i = S_i + \varphi_i,\ i = 1, 2, ..., N, \tag{9}$$

where T_i and S_i are the system tested data and simulation results, φ_i is a Gaussian random number with a mean

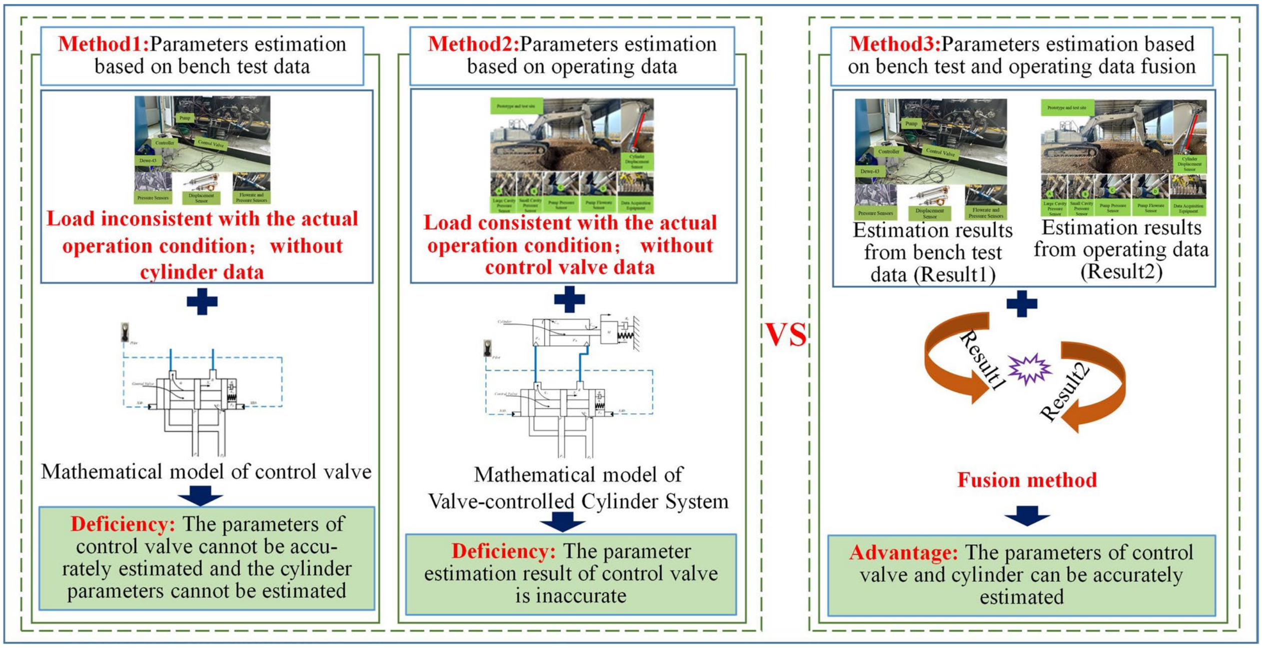


Figure 4 Comparison of different parameter estimation methods

value of zero and variance of σ^2, i is the time sample node number, and N is the total number of time sample nodes.

The maximum likelihood function of parameter estimates is as follows:

$$p\left(D|\theta,\sigma^2\right)=\frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(\frac{-1}{2\sigma^2}\sum_{i=1}^{N}\frac{(T_i-S_i)^2}{N}\right). \tag{10}$$

The mean square error (MSE) function between the simulation output data and system tested data is defined as:

$$Q=\frac{1}{N}\sum_{i=1}^{N}(T_i-S_i)^2. \tag{11}$$

Based on the likelihood function, the posterior estimation result of the parameters obtained by continuously updating the prior data is:

$$\begin{aligned}&p\left(\theta_j|D\right)=\int p\left(\boldsymbol{\theta},\sigma^2|D\right)\mathrm{d}\boldsymbol{\theta}_{-j}\mathrm{d}\sigma^2\propto\\&\int p\left(D|\boldsymbol{\theta},\sigma^2\right)p(\boldsymbol{\theta})\mathrm{d}\sigma^2\mathrm{d}\boldsymbol{\theta}_{-j},\end{aligned} \tag{12}$$

where j represents the parameter index, take as 1, 2, 3,…, p, p is the total number of parameters.

Eq. (12) is a general expression of the posterior probability distribution of θ_j, and it is not easy to obtain the analytical solution of independent samples through it [35, 36]. The relevant sample sequence representing a posterior distribution can be obtained by the Markov Chain Monte Carlo (MCMC) sampling method. The process is as follows [32, 37]:

(1) Set the total number of iterations N_n, 'burn in' iteration number N_b and parameter vector length p. Initialize the Markov chain k=0, extract the parameter vector from the parameter prior distribution $N(\boldsymbol{\theta})$: $\boldsymbol{\theta}^*(0)=(\theta_1^*,\theta_2^*,\ldots,\theta_p^*)$, define the random walk interval length L_j of each parameter, calculate $Q(\boldsymbol{\theta}^*(0))$ and the sample variance subject to the inverse gamma distribution [38]: $\sigma^2(0)=IG(N/2+1, Q(\boldsymbol{\theta}^*(0))/2)$;
(2) $k=k+1$, update each parameter in the parameter vector according to $\theta_j^*=\theta_j(k-1)+2L_j\times U(-1\ 1)$. Calculate the acceptance function $\alpha=p(\boldsymbol{\theta}_j^*)/p(\boldsymbol{\theta}_{j-1})\exp((-0.5/\sigma^2(k-1))\times(Q(\boldsymbol{\theta}^*)-Q(\boldsymbol{\theta}_{j-1})))$, where $\boldsymbol{\theta}^*=(\theta_1(k),\ldots,\theta_j^*,\theta_{j+1}(k-1),\ldots,\theta_p(k-1))$, $\boldsymbol{\theta}_{j-1}=(\theta_1(k),\ldots,\theta_{j-1}(k),\theta_j(k-1),\theta_{j+1}(k-1),\ldots,\theta_p(k-1))$;
(3) Generate a random number α_n in uniform distribution $U(0\ 1)$. When $\alpha_n<\alpha$, $\theta_j(k)=\boldsymbol{\theta}^*$, $L_j=1.01L_j$; otherwise, $\theta_j(k)=\theta_j(k-1)$, $L_j=L_j/1.007$;
(4) After each iteration completes the parameter update, calculate $Q(\theta(k))$, and extract the random number from the inverse gamma distribution $IG(N/2+1, Q(\theta(k))/2)$ as the variance $\sigma^2(k)$ of the kth iteration, where $\boldsymbol{\theta}(k)=(\theta_1(k),\theta_2(k),\theta_3(k),\ldots,\theta_p(k))$;
(5) Repeat steps (2) to (4). Stop L_j adjustment when $k>N_b$; when $k>N_n$, stop the update of θ_j^*. Remove

the results of the previous N_b iteration and record the remaining parameter vector $\boldsymbol{\theta}$ as the posterior distribution $p\,(\theta)$ of the parameter.

Based on Bayesian theory and the MCMC sampling method, the prior distribution ($prior_1$, $prior_2$ and $prior_3$) for each parameter is obtained separately using bench test and operating data as benchmarks. The pooling method is then applied to fuse the different prior information, followed by another round of Bayesian inference to estimate the model parameters. This process yields the final estimates of the model parameters ($\boldsymbol{\theta_1}$, $\boldsymbol{\theta_2}$) and determines the contribution of each type data through weighting coefficients k_1. This constitutes the methodology for estimating model parameters by combining bench test and operating data. The specific implementation steps are as follows:

Step 1: Assume that the initial prior distribution of the control valve model parameters is a uniform distribution $U1\,(\theta_{1j_1}^L\,\theta_{1j_1}^U)$, according to the empirical values in Table 1. Here, $\theta_{1j_1}^L$ represents the minimum values for the control valve j_1th parameter, $\theta_{1j_1}^U$ represents the maxmum values for the control valve j_1th parameter, and j_1 takes values of 1, 2,..., 4. Based on the bench test data of the control valve, the distribution of the control valve model parameters ($prior_1$ ($\boldsymbol{\theta}_1$)) is obtained through Bayesian theory, which is an estimated value lacking actual load information.

Step 2: Similarly, the control valve and hydraulic cylinder parameters are set as uniform distributions $U1$ $(\theta_{1j_1}^L\,\theta_{1j_1}^U)$ and $U2$ $(\theta_{1j_2}^L\,\theta_{1j_2}^U)$, respectively, based on the empirical values provided in Table 1. Here, $\theta_{1j_2}^L$ represents the minmum value for the cylinder j_2th parameter, $\theta_{1j_2}^U$ represents the maxmum value for the cylinder j_2th parameter, and j_2 takes values of 1, 2,..., 4. Based on the operating data of the cylinder, the distribution of the control valve and cylinder parameters ($prior_2$ ($\boldsymbol{\theta}_1$) and $prior_3$ ($\boldsymbol{\theta}_2$)) are obtained through Bayesian theory. These distributions incorporate actual load information.

Step 3: After obtaining the distributions of the control valve parameters ($prior_1$ ($\boldsymbol{\theta}_1$) and $prior_2$ ($\boldsymbol{\theta}_1$)), a geometric pooling method [17] is employed to fuse these distributions, ensuring that the parameter estimates encompass both the control valve output data and the actual load information. The pooled result is denoted as *prior**:

$$
\begin{aligned}
prior*(\boldsymbol{\theta_1}) &= \prod_{i=1}^{2} prior_i(\boldsymbol{\theta_1})^{k_i} \\
&= prior_1(\boldsymbol{\theta_1})^{k_1} prior_2(\boldsymbol{\theta_1})^{1-k_1},
\end{aligned}
\tag{13}
$$

where k_i is the weight coefficient, representing the contribution of $prior_i$ to *prior**, $\sum_{i=1}^{2} k_i = 1$, and its prior distribution can be set as a uniform distribution $U\,(0, 1)$ [21].

Step 4: Take the distributions *prior**($\boldsymbol{\theta}_1$) and $prior_3$ ($\boldsymbol{\theta}_2$) as new prior information and take the cylinder operating data as the benchmark to estimate the system model parameters through Bayesian theory. Obtain the final estimated values of the system model parameters vector $\boldsymbol{\theta_1}$, $\boldsymbol{\theta_2}$ and weight coefficient vector $\boldsymbol{k_1}$. The process is shown in Figure 5.

In Figure 5, $prior_1$ ($\boldsymbol{\theta}_1$) and $prior_2$ ($\boldsymbol{\theta}_1$) and $prior_3$ ($\boldsymbol{\theta}_2$) are obtained using the MCMC sampling method based

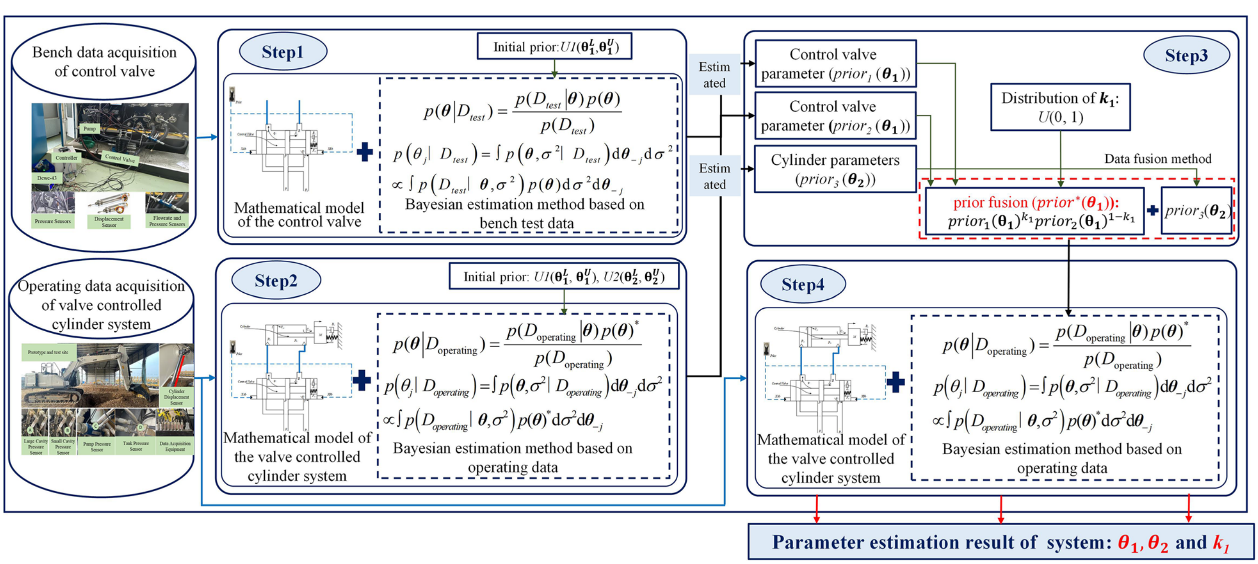


Figure 5 Valve-controlled cylinder system parameter estimation based on the data fusion method

on the Bayesian posterior estimation in Eq. (12). The Bayesian posterior estimation expression in Step 4 is updated to Eq. (14). The estimation results of the system model parameters vector $\boldsymbol{\theta}_1$, $\boldsymbol{\theta}_2$ and weight coefficient vector $\boldsymbol{k}_1$ are also obtained through the MCMC sampling method.

$$\begin{aligned} &p\left(\theta_j|D\right) = \int p\left(\theta, \sigma^2|D\right) \mathrm{d}\theta_{-j} \mathrm{d}\sigma^2 \\ &\propto \int p\left(D|\theta, \sigma^2\right) prior * (\theta_{j1}) \\ &prior_3(\theta_{j2}) \mathrm{d}\sigma^2 \mathrm{d}\theta_{-j1} \mathrm{d}\theta_{-j2}. \end{aligned} \tag{14}$$

4 Data Acquisition

4.1 Operating Data Acquisition

The operating data acquisition test was conducted at an excavator manufacturing company's standard test site, which complies with testing standards. A prototype of a medium-sized positive flow control system excavator [39, 40] was employed for the experiment, primarily targeting data acquisition such as main pump pressure, boom cylinder pressure and displacement. Detailed information regarding the measurement points is provided in Table 2. Data was recorded and stored via a Dewe-43 data acquisition device with a frequency of 500 Hz.

The test conditions comprised three types: single action of the boom using fast operation, single action of the boom using slow operation, and excavation operation. They are known simply as fast boom operation, slow boom operation, and excavation. During fast boom operation conditions, the pilot signal resemble a step, while slow boom operation conditions resemble a ramp signal. The excavation condition utilises ordinary soil as the working material. Each test consisted of three cycles, and a total of 20 tests were performed for each operation condition. The experimental arrangement is depicted in Table 3.

Among the three operation conditions, the excavation operation load is the worst, followed by the fast boom operation, while the slow boom operation is the most stable. The experimental site and sensor layout are illustrated in Figure 6.

Table 2 Measurement point details

Measurement points	Sensors performance
Pump pressure	Range: 0–60 MPa, Accuracy: ±0.5%F.S
Tank pressure	Range: 0–20 MPa, Accuracy: ±0.5%F.S
Boom large cavity pressure	Range: 0–60 MPa, Accuracy: ±0.5%F.S
Boom small cavity pressure	Range: 0–60 MPa, Accuracy: ±0.5%F.S
Boom cylinder displacement	Range: 0–3000 mm, Accuracy: ±0.015%F.S.

4.2 Bench Test Data Acquisition

Bench test data collection for the control valve was carried out in accordance with the parameter estimation requirements of the model for the valve-controlled cylinder system. A pump-valve test bench was utilized to perform load simulation on the pump and control valve, enabling concurrent measurement of the control valve spool displacement (x_v) and flow rates (q_1 (q_2)) through the valve ports. The pump-valve test bench principle is depicted in Figure 7(a). In the test, the motor drives the pump, while the boom valve and pump are controlled by the pilot pressure (P_{pilot}). The control valve load is set using Po1, measured via P2, while the pump's outlet pressure is measured by pressure sensor P1. Valve flow rate and spool displacement are collected by flow rate sensor Q1 and displacement sensor Xs, respectively. Pilot pressure (Ppilot) is collected by pressure sensor P3. All test data are recorded using Dewe-43 data acquisition equipment. Figure 7(b) illustrates the arrangement of the test bench.

Similarly, the test bench primarily collected experimental data on the boom cylinder control valve under fast boom operation conditions, slow boom operation conditions, and excavation conditions. The pilot signals for each condition are the same as those used during operating data acquisition experiments. The maximum load of the control valve is set to 300 bar. Each test consisted of 3 cycles, and 20 tests were performed for each operation condition. Detailed information about the measurement points of the bench test is presented in Table 4.

Table 3 Experimental conditions description

Conditions	Pilot signal	Excavated material	Experimental number
Fast boom operation	Step signal	Idle condition	3 cycles/time, 20 times
Slow boom operation	Slope signal	Idle condition	3 cycles/time, 20 times
Excavation operation	Excavation operation pilot signal	Ordinary soil	3 cycles/time, 20 times

Figure 6 Experiment for operating data acquisition

5 Results and Discussion

5.1 Parameter Estimation Results for Slow Operating Conditions

Using the slow operating condition as a case study, this paper conducts an in-depth analysis and discussion on the estimation of model parameters in the valve-controlled cylinder system. The obtained parameter estimation results are fitted to a normal distribution. When the bench test and operating data are taken as references respectively, the estimation results of the control valve parameters are shown in Figure 8 as $prior_1$ and $prior_2$. The parameter estimation result of the control valve, obtained using the data fusion method, is shown as $fusion_v$ in Figure 8. It can be seen from Figure 8 that $prior_1$, $prior_2$ and $fusion_v$ of each parameter have different distributions. $Prior_2$ exhibits the highest variance, displaying a dispersed distribution, while $prior_1$ demonstrates a comparatively smaller variance and a more centralized distribution. $Fusion_v$ exhibits a mean value in proximity to that of $prior_2$, while its variance closely resembles that of $prior_1$. High consistency exists between the frequency distribution histogram and the probability density curve of $fusion_v$, indicating the stability and accuracy of parameter estimation results derived from the data fusion method. Adopting the mean value of $fusion_v$ as the final estimated parameters for control valve.

The 95% confidence interval of the control valve parameter estimation results before and after the fusion method is shown in Figure 9. It can be seen from Figure 9 that the confidence intervals of $prior_1$, $prior_2$ and $fusion_v$ are different, and the relationship between their confidence intervals is $prior_1\_interval<fusion_v\_interval <prior_2\_interval$. Although the B_v confidence interval result differs from the above conclusion, the B_v confidence interval range is small, and the gap between them can be ignored.

To obtain the mean values and 95% confidence intervals for each weight coefficient, as shown in Figure 10. Taking the mean value as the estimation result of the weight coefficient, k_{1Cq} is 0.382, indicating that the bench test data has a small contribution to the estimation result of C_q. In contrast, the operating data have a significant contribution to them. This result is consistent with the characteristics that C_q is greatly affected by the load. However, k_{1Bv} and k_{1Kv} are all close to 0.5, indicating that the contributions of the bench test and operating data to the estimation results of B_v and K_v are equal. This seems to be related to the fact that they are the inherent attribute parameters of the control valve. The value of k_{1F0} is 0.456, and the contribution of the operating data to the estimated result is slightly higher than that of the bench test data.

Before and after applying the data fusion method, the estimation of cylinder parameters is based on cylinder operating data, while the prior information remains the same. The estimation result of the cylinder parameters $prior_3$ and $fusion_c$ exhibit little change, as shown in Figure 11. The slight change in cylinder parameters is caused

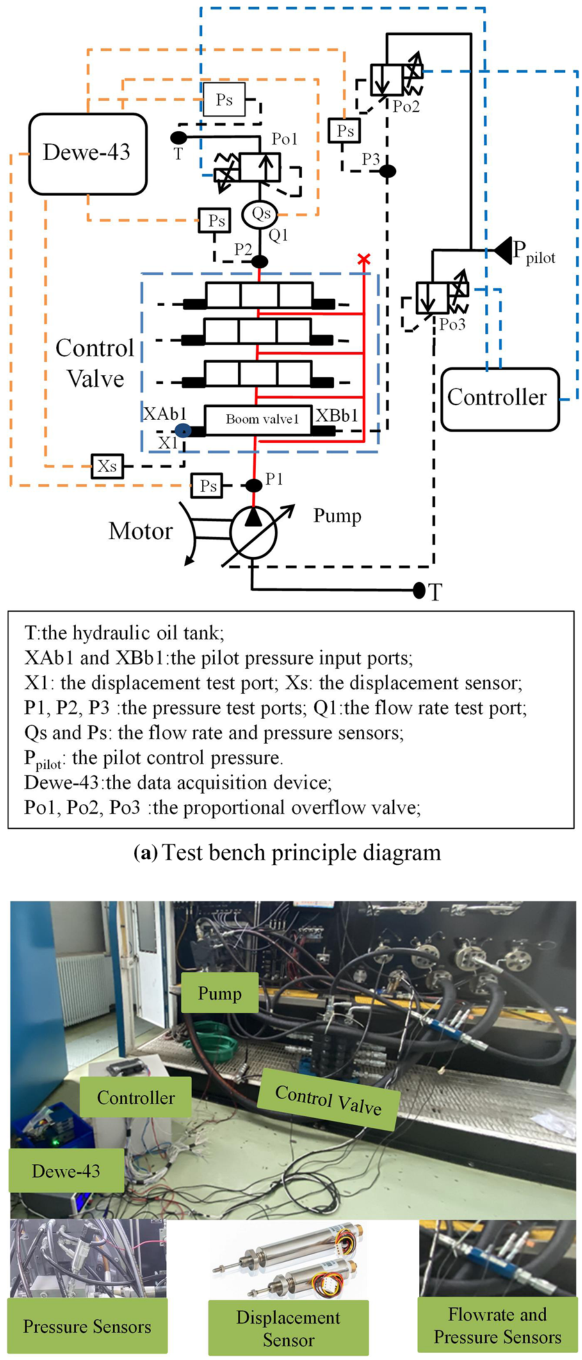


Figure 7 Test bench description: (**a**) Test bench principle diagram, (**b**) Test bench picture

by the change in parameters C_q before and after the data fusion method. They are connected through the flow rate continuity equation.

Figure 12 presents the 95% confidence intervals of the cylinder estimated parameters. Similarly, the confidence intervals exhibit small deviation, the variation in C_q likewise influences the differences between them.

Table 4 Bench test measurement point details

Measurement points	Sensor performance
Pump pressure	Range: 0–60 MPa, Accuracy: ±0.5%F.S
Control valve flow rate	Range:16–600 L/min, Accuracy: ±0.5%F.S.
Control valve pressure	Range: 0–60 MPa, Accuracy: ±0.5%F.S
Valve spool displacement	Range: 0–15 mm, Accuracy: ±0.5%F.S

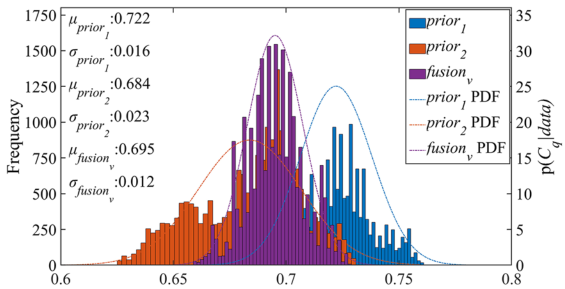
5.2 Parameter Estimation Results of Other Conditions

Using the same method, the parameters of the valve-controlled cylinder system model were estimated and analyzed under fast boom operation and excavation conditions. The estimation results under fast boom operation conditions are shown in Tables 5, 6 and 7. While the parameter estimates and weight coefficients slightly differ from those obtained under slow boom operation conditions, it can be observed from the tables that they exhibit similar trends.

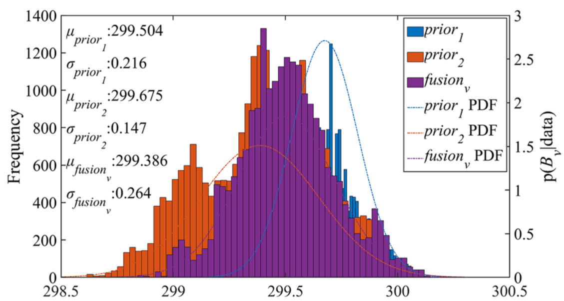
The estimation results under excavation operation conditions are shown in Tables 8, 9 and 10. Although the estimated values differ between fast and slow boom operation conditions, they exhibit similar trends.

5.3 Comparison of Different Parameter Estimation Methods

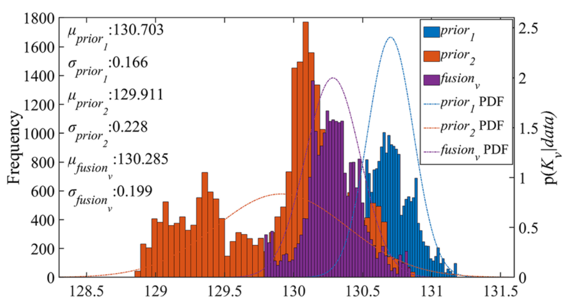
Based on the data obtained in Section 4, the parameter estimation of the system model is studied through the data fusion method, the Bayesian method [33, 38] and the PSO algorithm [2]. Notably, the latter two methods utilize cylinder operating data as their benchmark. Subsequently, leveraging the outcomes of the parameter estimation, a simulation model is developed to compute the cylinder displacement across diverse working conditions, and compare the model calculation results with the test results, as shown in Figure 13. It can be seen from Figure 13 that for all working conditions, the results of the parameter estimation method using the PSO algorithm have the worst coincidence with the test results. The above research has demonstrated that bench test and operating data contribute significantly to estimating control valve parameters. Due to the difficulty in collecting operating data of the control valve, the parameter estimation process based on operating data and the Bayesian method lacks information regarding the control valve. Additionally, the displacement data of the hydraulic



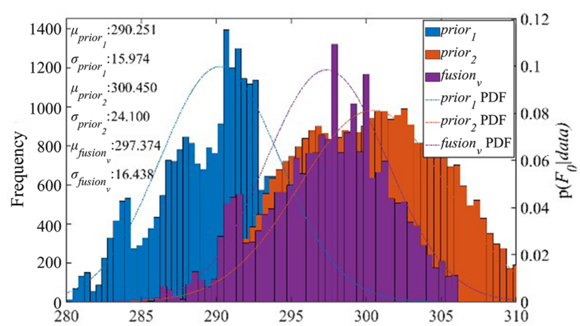
(a) $prior_1$, $prior_2$ and $fusion_v$ results of C_q



(b) $prior_1$, $prior_2$ and $fusion_v$ results of B_v



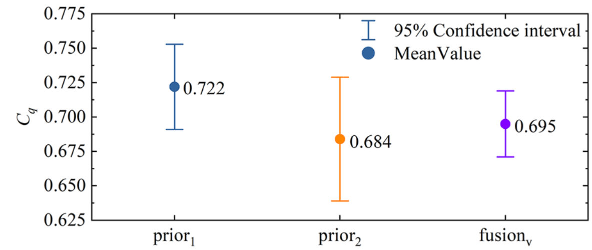
(c) $prior_1$, $prior_2$ and $fusion_v$ results of K_v



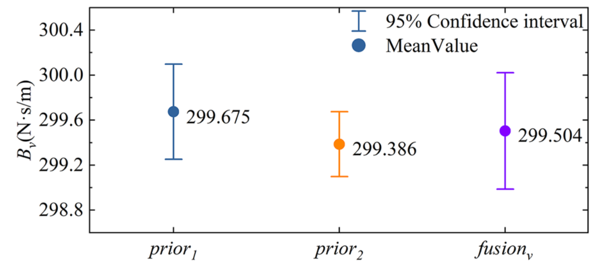
(d) $prior_1$, $prior_2$ and $fusion_v$ results of F_0

Figure 8 Estimation results for the control valve parameters

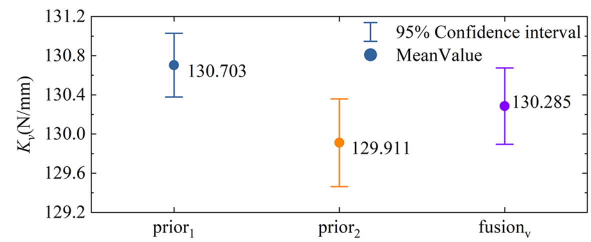
cylinder is not a direct measurement of the control valve, leading to biases in the estimated control valve parameters and affecting the accuracy of the valve-controlled cylinder system model. The data fusion method integrates the actual load data and the control valve output data, making the parameter estimation results more accurate.



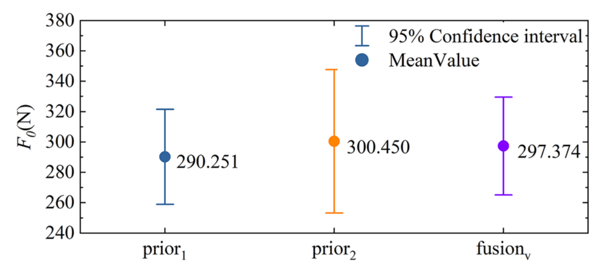
(a) 95% confidence interval of C_q



(b) 95% confidence interval of B_v



(c) 95% confidence interval of K_v



(d) 95% confidence interval of F_0

Figure 9 95% confidence intervals of control valve parameter estimation results

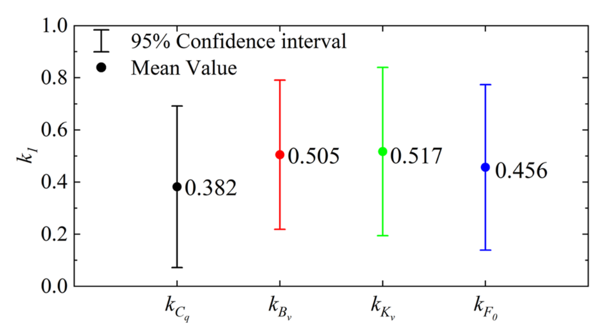


Figure 10 95% confidence interval of $\boldsymbol{k}_1$

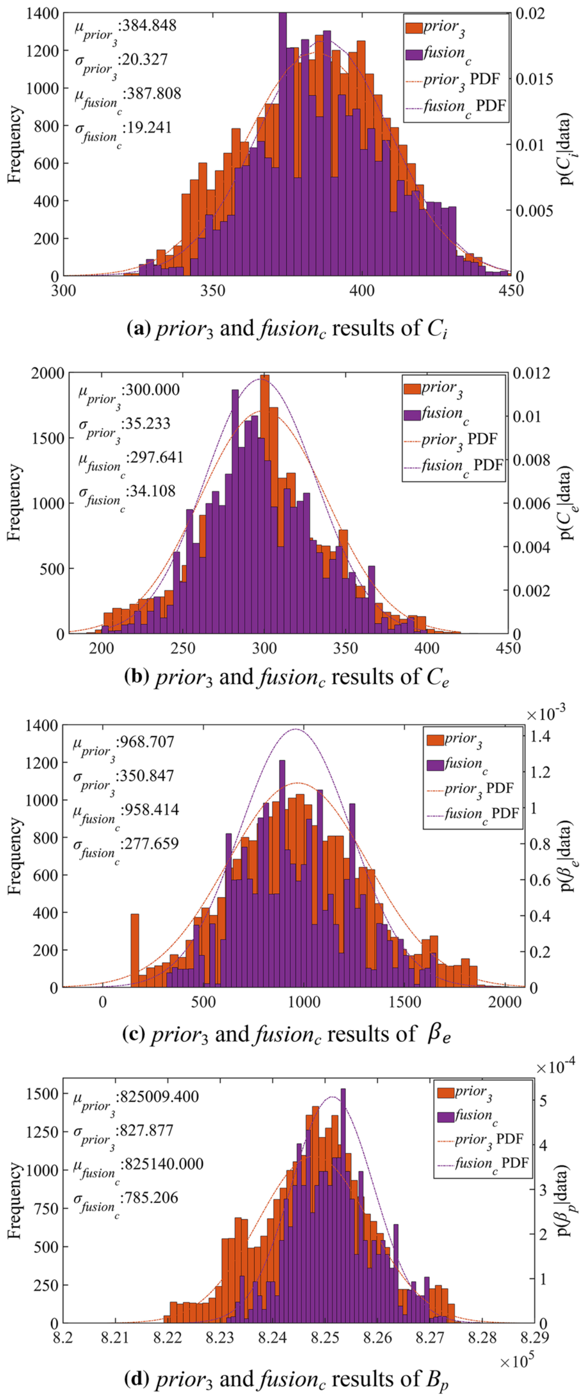


Figure 11 Estimation result for cylinder parameters

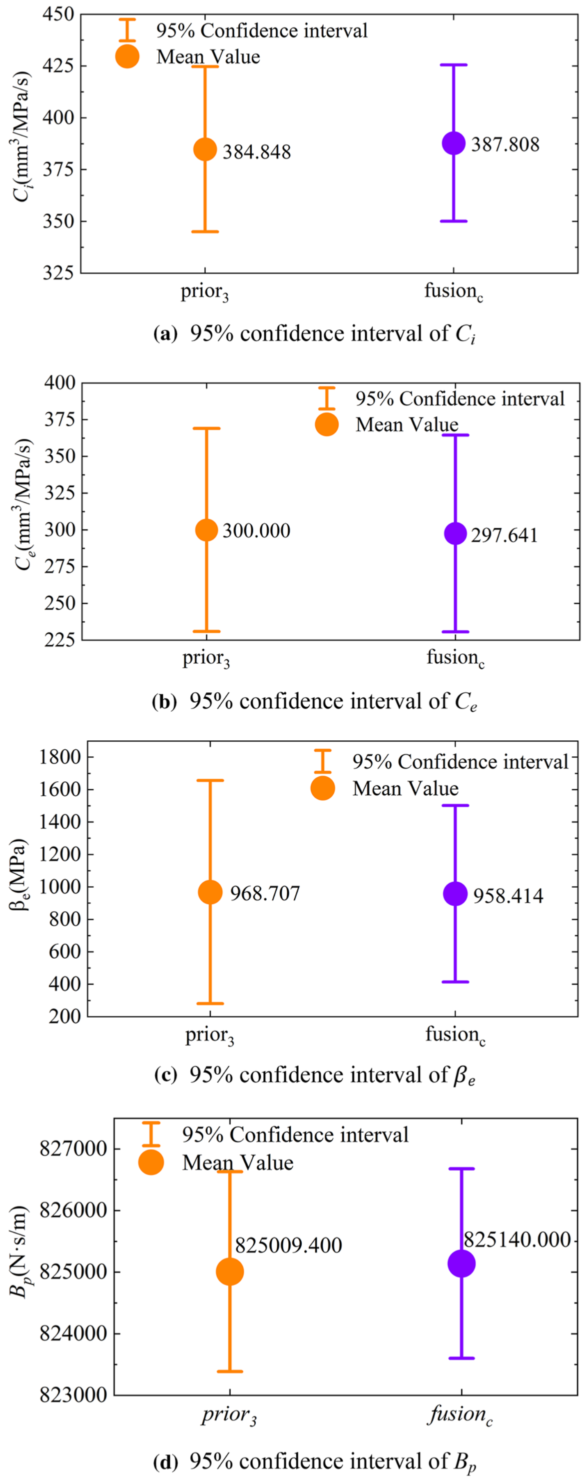


Figure 12 Cylinder parameter estimation results' 95% confidence intervals

Consequently, the simulation results of the valve-controlled cylinder system model-based data fusion method exhibit good agreement with the test results.

Each parameter estimation method's model accuracy value Q is calculated using Eq. (11), and the results are listed in Table 11.

In all working conditions, the relationship between the model accuracy obtained using the three methods is $Q_{fusion}<Q_{bayesain}<Q_{PSO}$, indicating that the model

Table 5 Parameter estimation results of control valve under fast boom operation conditions

Models	Results	C_q	B_v	K_v	F_0
$Prior_1$	95% confidence interval	[0.688 0.762]	[299.352 300.108]	[130.328 131.128]	[260.142 322.860]
	Mean value	0.725	299.730	130.728	291.501
$Prior_2$	95% confidence interval	[0.642 0.725]	[299.108 299.694]	[129.064 130.158]	[254.234 347.906]
	Mean value	0.6835	299.401	129.611	301.070
$Fusion_v$	95% confidence interval	[0.673 0.723]	[298.977 300.001]	[129.705 130.525]	[266.306328.612]
	Mean value	0.698	299.489	130.115	297.459

Table 6 Parameter estimation results of weight coefficients under fast boom operation conditions

Results	k_{1Cq}	k_{1Bv}	k_{1Kv}	k_{1F0}
95% confidence interval	[0.082 0.602]	[0.221 0.798]	[0.204 0.854]	[0.129 0.754]
Mean value	0.342	0.510	0.529	0.442

Table 7 Parameter estimation results of cylinder under fast boom operation conditions

Models	Results	C_i	C_e	β_e	B_p
$Prior_3$	95% confidence interval	[346.107 425.289]	[231.243 370.517]	[285.347 1661.267]	[823461.461 826713.539]
	Mean value	385.698	300.880	973.307	825087.500
$Fusion_c$	95% confidence interval	[351.056 426.120]	[231.289 365.693]	[418.262 1510.826]	[823685.996 826719.254]
	Mean value	388.588	298.491	964.544	825202.625

Table 8 Parameter estimation results of control valve under excavation operation conditions

Models	Results	C_q	B_v	K_v	F_0
$Prior_1$	95% confidence interval	[0.689 0.750]	[299.352 300.298]	[130.678 131.130]	[259.142 322.160]
	Mean value	0.720	299.825	130.904	290.651
$Prior_2$	95% confidence interval	[0.642 0.728]	[299.228 299.924]	[129.144 130.628]	[253.514 347.886]
	Mean value	0.685	299.576	129.886	300.700
$Fusion_v$	95% confidence interval	[0.674 0.722]	[299.157 300.121]	[130.130 130.585]	[266.326 329.452]
	Mean value	0.698	299.639	130.358	297.889

Table 9 Parameter estimation results of weight coefficients under excavation operation conditions

Results	k_{1Cq}	k_{1Bv}	k_{1Kv}	k_{1F0}
95% confidence interval	[0.078 0.670]	[0.216 0.788]	[0.198 0.850]	[0.164 0.738]
Mean value	0.374	0.502	0.524	0.451

accuracy based on the data fusion method is the highest. Moreover, $\Delta Q_{maxfusion}<\Delta Q_{maxBayesain}<\Delta Q_{maxPSO}$, indicating that the parameter estimation result based on the data fusion method is the most stable. In addition, the relationship between the model accuracy values of different operation conditions in all methods is $Q_{Slow}< Q_{Fast}< Q_{Excavation}$, indicating that the worse the working conditions, the worse the model accuracy. This proves the critical role of the data fusion method.

Table 10 Parameter estimation results of cylinder under excavation operation conditions

Models	Results	C_i	C_e	β_e	B_p
$Prior_3$	95% confidence interval	[346.107 423.766]	[231.023 370.157]	[290.547 1665.167]	[823382.761 826783.039]
	Mean value	384.9365	300.590	977.857	825082.900
$Fusion_c$	95% confidence interval	[352.196 426.252]	[230.789 364.493]	[420.202 1518.626]	[823663.596 826792.504]
	Mean value	389.224	297.641	969.414	825228.050

6 Conclusions

To effectively use the advantages of bench test and operating data in research on the estimation of simulation model parameters, this paper proposed a model parameter estimation method for bench test and operating data fusion based on Bayesian theory and pool method. By using the data fusion method, valve-controlled cylinder system model parameters estimation were studied, and the following research conclusions were drawn:

1 Taking slow boom operation conditions as an example, variance in estimation results based on operating data ($prior_2$) is the largest, while for bench test data ($prior_1$), it is small. $Prior_1$ and $prior_2$ have varying degrees of influence on $fusion_v$. The relationship between the confidence intervals of $prior_1$, $prior_2$ and $fusion_v$ is $prior_1$_interval< $fusion_v$_interval< $prior_2$_interval.

2 The weighting coefficient vector $\boldsymbol{k_1}$ was obtained for slow boom operation conditions. From the weight coefficient estimation results, the bench test data contribute less to the estimation results of C_q, while the operating data contribute more. The contribution of bench test and operating data to B_v and K_v estimation results is similar, and the contribution of operating data to F_0 estimation results is slightly higher than that of the bench test data.

3 Using operating data as a benchmark, it is possible to obtain relatively accurate estimates of the cylinder parameters, and there is a high level of consistency between $prior_3$ and $fusion_c$. After the data fusion method, the few changes in the parameter results are caused by changes in the C_q estimation results.

4 Parameters of the valve-controlled cylinder system model were estimated under fast boom operation and excavation conditions simultaneously. Estimated values of parameters slightly differ among the three conditions, yet exhibit consistent patterns and trends.

5 Compared with the Bayesian method and the PSO algorithm, the simulation model results based on the data fusion method coincide best with the test results, and the model accuracy is the highest. In addition, the worse the operation conditions, the more inaccurate the parameter estimation results. This proves the importance of data fusion in parameter estimation research.

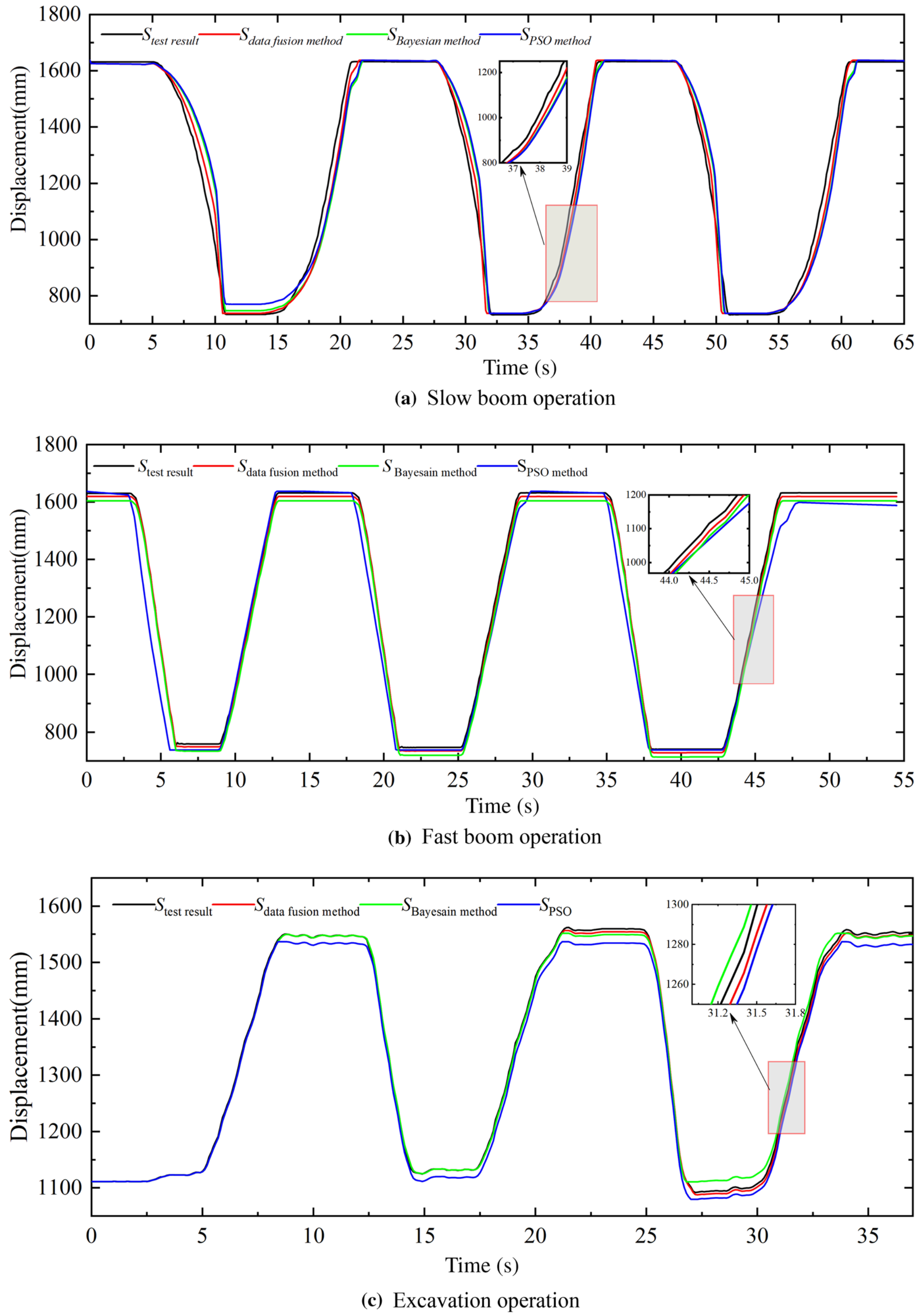


Figure 13 Comparison of cylinder displacement simulation results

Table 11 Model accuracy value results comparison

Method	Slow boom operation	Fast boom operation	Excavation operation	ΔQ_{max}
The Bayesian method	0.68	7.58	31.34	30.66
The data fusion method	0.26	1.73	2.92	2.66
The PSO algorithm	2.33	31.78	36.42	34.09

Acknowledgements
The authors would like to express their sincere gratitude to the engineers at Xuzhou XCMG Excavation Machinery Co., Ltd. and Xuzhou XCMG Research Institute Co., Ltd. for their valuable assistance during the experimentation process.

Authors' Contributions
DS, HL, XX and YX were in charge of the whole trial; DS wrote the manuscript; LH and SW helped revised the manuscript. LH contributed to the conception of the study. All authors read and approved the final manuscript.

Funding
Supported by National Key R&D Program of China (Grant Nos. 2020YFB1709901, 2020YFB1709904), National Natural Science Foundation of China (Grant Nos. 51975495, 51905460) and Guangdong Provincial Basic and Applied Basic Research Foundation of China (Grant No. 2021-A1515012286) and Science and Technology Plan Project of Fuzhou City of China (Grant No. 2022-P-022).

Data availability
The data that support the findings of this study are available on request from the author, Hou Liang, upon reasonable request.

Declarations

Competing Interests
The authors declare that they have no competing interests.

Received: 30 December 2022 Revised: 12 January 2024 Accepted: 2 April 2024
Published online: 30 April 2024

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