

Optimal parameter identification of hydro-pneumatic suspension for mine cars

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Abstract. This article proposes a method for matching parameters of hydro-pneumatic suspension with the goal of improving the vehicle ride comfort of mine cars. Considering the nonlinear characteristics of the hydro-pneumatic suspension, a 7-DOF dynamic model is established for the entire vehicle. The Kepler optimization algorithm is applied for parameter matching and simulation analysis of the hydro-pneumatic suspension based on vehicle ride comfort. Comparative verification shows that compared with the fitness functions of other algorithms, the KOA algorithm converges the fastest and has the highest precision in obtaining the optimal solution. After matching, there is a significant reduction in the suspension dynamic deflection, with the degree of attenuation for the four wheels at approximately 55.13%, the attenuation of vehicle body acceleration reduced by 12.7%, and the reduction in wheel dynamic load at around 10%, with a minimum of 3.16% for the right rear wheel and a maximum of 16.62% for the right front wheel. The KOA optimization algorithm exhibits significant advantages in parameter matching of hydro-pneumatic suspensions, resulting in a noticeable improvement in vehicle ride comfort.

Keywords: Hydro-pneumatic suspension / Kepler Optimization Algorithm (KOA) / vehicle ride comfort / parameter matching / nonlinear characteristics

1 Introduction

Mining cars can bear tens or even hundreds of tons of load under harsh mining road conditions, resulting in poor vehicle ride performance. To ensure work efficiency and personal safety, greater requirements are advanced for the suspension of mining cars. In the late 1960s, the hydro-pneumatic suspension was introduced into mining vehicles, which combined the variable stiffness of gas springs with the good damping characteristics of hydraulic dampers [1]. However, traditional passive hydro-pneumatic suspension cannot guarantee good vehicle ride under complex road conditions. Hence, both domestic and international scholars have embarked on in-depth investigations into the hydro-pneumatic suspension structural parameters.

Extensive research has been conducted globally on the optimization of structural parameters within suspension systems. Feng et al. [2] optimized the stiffness and damping coefficient of the hydro-pneumatic suspension

based on the improved PSO-GWO hybrid algorithm, and improved the ride comfort and body attitude. Xu et al. [3] employed the Latin hypercube method, in conjunction with particle swarm optimization, to analyze and refine the hydro-pneumatic suspension structural parameters, effectively improving the dynamic performance of the hydro-pneumatic suspension. Ji et al. [4] studied a hysteretic nonlinear system with random excitation, and solved the optimization objective function with the obtained probability density function by combining non-Gaussian truncation and cumulant truncation. Tian et al. [5] introduced an enhanced genetic algorithm aimed at optimizing the structural parameters of hydro-pneumatic suspensions. The findings demonstrated that the refined genetic algorithm effectively enhanced the vehicle's dynamic performance characteristics. Gomes et al. [6] optimized the hydro-pneumatic suspension nonlinear characteristics based on the PSO algorithm. Han et al. [7] used an improved synthetic fish flock algorithm to enhance the architectural parameters of suspensions and boost the anti-vibration efficiency of lorries with flexible wheels.

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The shortcomings of current research lie in the fact that most studies on parameter matching of hydro-pneumatic suspension have not fully considered their nonlinear characteristics during modeling, resulting in a significant gap between the model and reality. Moreover, current research generally focuses on single objective structural parameter optimization, which leads to optimization results that cannot fully reflect the overall performance of vehicle.

On the basis of previous research, this article fully considers the nonlinear characteristics of the hydro-pneumatic suspension in the vehicle dynamics model. The Kepler optimization algorithm is used to perform multi-objective optimization on the three parameters of the hydro-pneumatic suspension damping hole diameter, initial gas pressure of the accumulator, and initial gas volume with respect to the vertical acceleration of the vehicle body, suspension dynamic deflection, and wheel dynamic load, aiming at improving the vehicle ride comfort under different road excitations. Compared with other algorithms, the Kepler optimization algorithm can quickly converge to the global optimal solution in the solution space, and adapt to complex nonlinear parameter matching problems. Compared with other metaheuristic algorithms, the Kepler optimization algorithm, which is a mathematical model with strong nonlinear characteristics, has more advantages in parameter matching for hydro-pneumatic suspension.

2 Materials and methods

2.1 Nonlinear characteristics of hydro-pneumatic springs

The hydro-pneumatic spring uses the compressibility and elastic deformation of gas to absorb and disperse the impact force of the road surface, and uses the damping generated by the liquid flowing through the gap to attenuate the vibration, so that the vehicle can maintain a stable state. The structural principle of the hybrid hydro-pneumatic spring is shown in Figure 1.

Under normal circumstances, nitrogen is the main gas in the hydro-pneumatic spring air chamber, and the properties of nitrogen and ideal gas are similar. Therefore, the change in the gas state parameters approximately follows the ideal gas state equation [8]:

$$PV^r = c. \quad (1)$$

In equation (1), P is the nitrogen pressure, V is the gas volume, c is a constant value, and r is the gas polytropic index.

When it is loaded to the static equilibrium state under the action of a load, the gas pressure p_0 inside the hydro-pneumatic spring can be expressed as:

$$p_b = \frac{mg}{A_2}. \quad (2)$$

In equation (2), m is the sprung mass, and A_2 indicates the piston rod area.

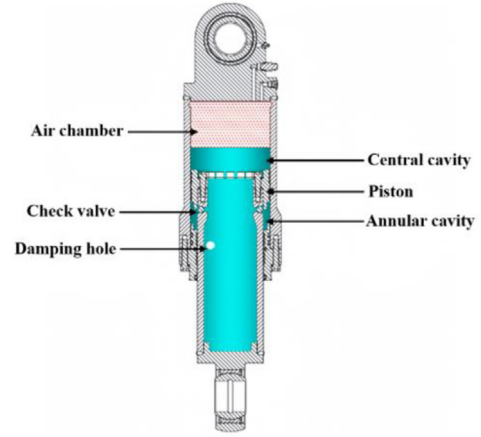


Fig. 1. Structural schematic diagram of the hybrid hydro-pneumatic spring.

In the static equilibrium state, nitrogen fully exchanges heat with the outside world, so this process is regarded as an isothermal change process, then the equation of state of the gas is as follows:

$$p_a V_a = p_b V_b. \quad (3)$$

In equation (3), p_a is the initial inflation pressure; V_a is the initial gas volume; p_b is the gas pressure of the hydro-pneumatic spring at static equilibrium; and V_b is the gas volume of the hydro-pneumatic spring at static equilibrium.

During the operation of the vehicle, owing to the continuous vibration of the vehicle, the gas in the hydro-pneumatic suspension air chamber switches back and forth in the state of compression and expansion. This procedure is considered an adiabatic procedure, and its formula of state is as follows:

$$p_b V_b^r = p_c V_c^r. \quad (4)$$

In equation (4), p_c is the pressure of gas at any position, and V_c is the gas volume at any position.

Taking the hydro-pneumatic spring position piston at the static balance of the vehicle as the origin, the internal instantaneous gas volume V_c during the running of the vehicle is:

$$V_c = V_b - A_2 y. \quad (5)$$

In equation (5), y is the distance traveled by the hydro-pneumatic spring piston at a certain moment.

Through equations (3), (4) and (5), the gas pressure within the hydro-pneumatic spring when the piston moves to any position is obtained:

$$p_c = p_b \left(\frac{V_b}{V_b - A_2 y} \right)^r = p_b \left(\frac{p_a V_a}{p_a V_a - p_b A_2 y} \right)^r. \quad (6)$$

Following the derivation process, the gas pressure within the hydro-pneumatic spring at any given position can be ascertained through the piston's movement. The elastic force exerted by the hydro-pneumatic spring under

this specific displacement can subsequently be determined as follows:

$$F_k = p_c \times A_2 = mg \left(\frac{p_a V_a}{p_a V_a - mgy} \right)^r. \quad (7)$$

The hydro-pneumatic spring stiffness can be obtained by differentiating the elastic force with respect to the displacement:

$$K = \frac{dF_k}{dy} = \frac{(mg)^2 r (p_a V_a)^r}{(p_a V_a - mgy)^{r+1}}. \quad (8)$$

In equation (8), k is the hydro-pneumatic spring stiffness.

When the hydro-pneumatic spring is in the stretching action, the check valve stops flowing, and the oil flows from the annular cavity through the damping orifice into the central cavity. The flow rate is as follows:

$$Q = A_3 v. \quad (9)$$

In equation (9), Q is the volumetric flow rate passing through the damping orifice, and A_3 is the area of the ring cavity.

The pressure difference before and after the oil flows through the damping orifice can be obtained from the flow formula of the thin wall orifice:

$$\Delta p_1 = \frac{\rho}{2} \left(\frac{Q}{C_d A_d} \right)^2. \quad (10)$$

In equation (10), ρ is the oil density, usually 860 kg/m³; C_d is the damping orifice flow coefficient; and A_d is the area of the damping orifice.

The damping force of the tensile stroke is as follows:

$$F_{c1} = \Delta p A_3 = \frac{\rho A_3^3 v^2}{2 C_d^2 A_d^2}. \quad (11)$$

During compression of the hydro-pneumatic spring, the check valve is opened, and the oil flows from the central cavity through the damping orifice and the check valve into the annular cavity. The resulting front and rear pressure difference is as follows:

$$\Delta p_2 = \frac{\rho}{2} \left(\frac{Q}{C_d A_d + C_f A_f} \right)^2. \quad (12)$$

In equation (12), C_f is the check valve flow coefficient and A_f is the check valve effective flow area.

The damping force generated during the compression stroke of the hydro-pneumatic suspension is as follows:

$$F_{c2} = \Delta p A_3 = \frac{\rho A_3^3 v^2}{2 (C_d A_d + C_f A_f)^2}. \quad (13)$$

In summary, the damping force of the stretching and compression action is unified as:

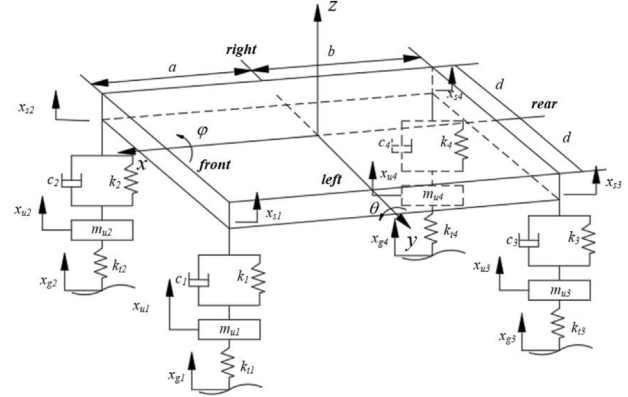


Fig. 2. 7-DOF vehicle dynamics diagram.

$$F_c = \frac{\rho A_3^3 v^2 \operatorname{sgn}(v)}{2 \{ C_d A_d + C_f A_f [0.5 + 0.5 \operatorname{sgn}(v)] \}^2}. \quad (14)$$

In equation (14), $\operatorname{sgn}(v)$ is a symbolic function. When the hydro-pneumatic spring is compressed, $v \geq 0$, $\operatorname{sgn}(v) = 1$; when it is stretched, $v < 0$, $\operatorname{sgn}(v) = -1$.

2.2 7-DOF vehicle dynamics model

This article takes a two-axle mining vehicle as the research object. Based on the 7-DOF vehicle dynamics diagram in Figure 2, the following derivation is made for the vehicle dynamics equation.

The body vertical force balance equation, and roll and pitch torque balance equation are as follows:

$$\begin{cases} m_s \ddot{x}_s = F_1 + F_2 + F_3 + F_4 \\ I_p \ddot{\theta} = -a(F_1 + F_2) + b(F_3 + F_4) \\ I_r \ddot{\phi} = d(F_1 + F_3) - d(F_2 + F_4). \end{cases} \quad (15)$$

The suspension's vertical force balance equation is presented, incorporating the nonlinear characteristics of the suspension into the 7-DOF dynamics model. The damping and elastic forces are considered as the suspension system output forces.

$$\begin{cases} m_{ui} \ddot{x}_{ui} = k_{ti}(x_{gi} - x_{ui}) - F_i; i = 1, \dots, 4 \\ F_i = c_i(\dot{x}_{ui} - \dot{x}_{si}) + k_i(x_{ui} - x_{si}); i = 1, \dots, 4 \end{cases} \quad (16)$$

The vertical displacement relationship among the mass centers of the four wheels is described as follows:

$$\begin{cases} x_{s1} = x_s - a \sin \theta + d \sin \phi \\ x_{s2} = x_s - a \sin \theta - d \sin \phi \\ x_{s3} = x_s + b \sin \theta + d \sin \phi \\ x_{s4} = x_s + b \sin \theta - d \sin \phi \end{cases} \quad (17)$$

In equations (15)–(17), m_s is the sprung mass; m_{ui} is the unsprung wheel mass; x_s is the car body vertical

Table 1. Vehicle parameters.

References	Structure parameters	Parameter value
[1]	Sprung mass (kg)	51200
[2]	Pitch inertia moment (kgm^2)	2440
[3]	Roll inertia moment (kgm^2)	3800
[4]	Front axle mass of unsprung (kg)	280
[5]	Rear axle mass of unsprung (kg)	475
[6]	Front wheel equivalent stiffness (N/m)	1.86e6
[7]	Rear wheel equivalent stiffness (N/m)	1.86e6
[8]	Wheelbase (m)	5.4
[9]	Distance from mass center to front wheels (m)	2.8
[10]	Distance from mass center to rear wheels (m)	2.6
[11]	Wheelbase (m)	2.3

displacement; x_{ui} is the unsprung vertical displacement; x_{gi} is the road surface vertical displacement; F_i , $i=1, \dots, 4$ is the output force of the suspension; c_i is the coefficient of damping; k_i is the stiffness of suspension; I_p is the car body pitch inertia moment; θ is the pitch angle; I_r is the car body roll inertia moment; φ is the roll angle; a , b are the length from the body's gravity center to the front and back axles; and d is half the wheel base.

2.3 Simulation settings

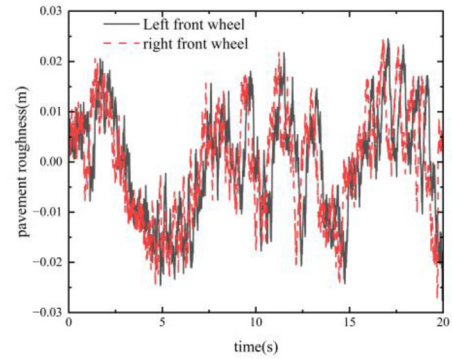
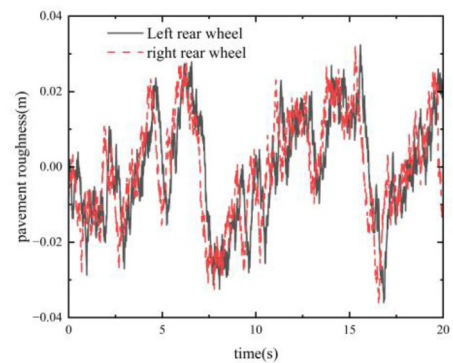
This article conducts simulation research on the implementation of Simulink function in MATLAB software. Table 1 lists the specific vehicle parameters.

Taking random road excitation as the vehicle dynamics model input, the power spectral density of different road grades is different at the corresponding reference spatial frequency, and the higher the road grade is, the greater the value and the more uneven the road surface. The random pavement structure formula is shown in equation (18) [9]:

$$\dot{q}(t) = -2\pi n_1 u q(t) + 2\pi n_0 w \sqrt{G_q(n_0)} v. \quad (18)$$

In equation (18), $\dot{q}$ is the vertical velocity spectrum of road roughness; v is the constant vehicle speed; n_0 is the reference spatial frequency, and 0.1 m^{-1} is used in this article. $G_q(n_0)$ is the coefficient of pavement roughness; n_1 is the lowest frequency in space, and 0.01 m^{-1} is used in this article. w is a white noise signal.

This article postulates that the mining vehicle travels consistently along a rectilinear path at a constant velocity of 20 meters per second. The road surfaces exhibit disparities on the left and right sides of the vehicle, whereas there is a temporal lag between the road surfaces encountered by the front and rear wheels on the same side. The configurations of the left and right front and rear wheels for the C-class pavement are depicted in Figures 3 and 4. The speed spectrum of the pavement is characterized as white noise, and the vertical roughness of the pavement ranges from -20 mm to 20 mm .

**Fig. 3.** Front wheel C-level pavement roughness.**Fig. 4.** Rear wheel C-level pavement roughness.

3 Kepler optimization algorithm

Inspired by the fundamental laws of physics, specifically Kepler's laws of planetary motion, the Kepler Optimization Algorithm (KOA) emerges as a metaheuristic approach. This algorithm mimics the positions and velocities of planets across various time intervals, where each planet represents a potential solution candidate.

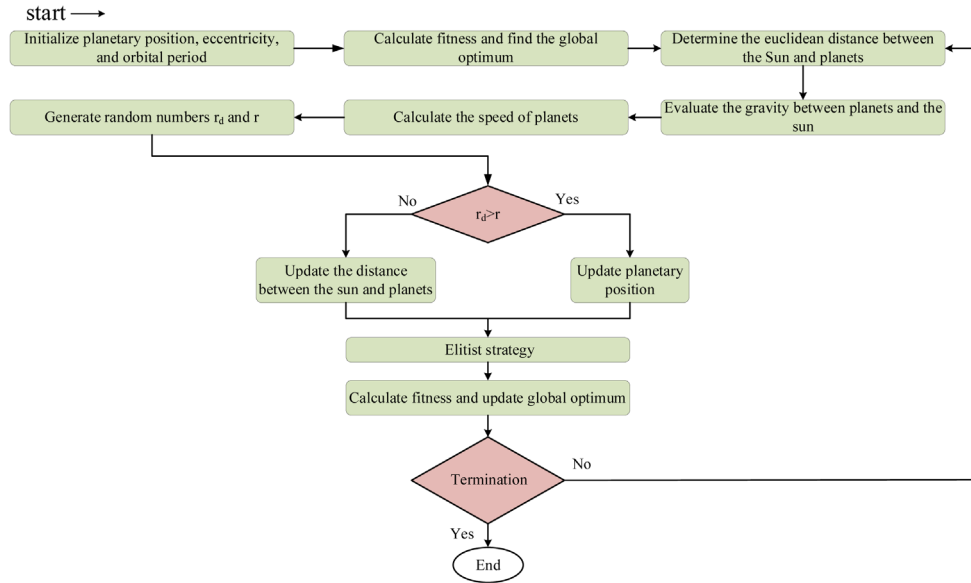


Fig. 5. Flowchart of KOA.

During the optimization process, these candidate solutions are randomly updated, relative to the current optimal solution, analogous to the sun in Kepler's system. The KOA realizes more effective exploration and the search space utilization by introducing multiple planet candidate solutions because these planets will present different states at different times, which is conducive to global optimization. In the optimization process, the algorithm adopts the following rules, and the optimization algorithm process is shown in [Figure 5](#) [10].

3.1 Optimization objective

In the realm of academic research on mining vehicles, ride comfort is primarily dictated by three key factors: vertical acceleration of the vehicle body, dynamic deflection of the suspension system, and dynamic load of the wheels. Notably, the vertical acceleration of the body serves as the primary determinant in assessing overall ride comfort. Consequently, in the present study, these three indicators are selected as the primary optimization objectives to enhance the ride comfort of mining vehicles. Since the dimensions of the three indicators are different, this article performs dimensionless processing for each indicator and sums the weighted coefficients of the three indicators after dimensionality processing as the objective function, as shown in equation (19):

$$\tau = \min \left(w_1 \frac{\text{rms}(a)}{\text{rms}(a_0)} + w_2 \frac{\text{rms}(f)}{\text{rms}(f_0)} + w_3 \frac{\text{rms}(F)}{\text{rms}(F_0)} \right). \quad (19)$$

In equation (19), a_0 and a are the vertical accelerations of the front and rear body matching parameters, f_0 and f are the parameters matching the dynamic deflections of the front and rear suspensions, and F_0 and F are the parameters matching the dynamic loads of the front and rear wheels. rms is the root mean square of each index. w_1 , w_2 and w_3 are the weighting coefficients of the subobjective

Table 2. Optimization variables and ranges.

Variables	Levels		
	1	2	3
p_a (MPa)	2.5	5	7.5
V_a (L)	2.29	4.5	6.87
D_d (mm)	2.5	5	7.5

function. Considering the importance of different indicators under actual working conditions, this article sets three weights of 0.5, 0.3, and 0.2, respectively.

3.2 Optimization variable

The selected optimization variables encompass the initial charging pressure (p_a), initial volume of gas (V_a) and damping orifice diameter of the hydro-pneumatic spring (D_d). Due to the distribution of vehicle axle loads, the vertical loads imposed on the front and rear axles typically vary in magnitude. The initial values of the optimization variables and defined optimization range are shown in [Table 2](#).

3.3 Constraint condition

To make the optimization results more realistic, engineering experience is applied as a constraint condition to the algorithm, and the mathematical model pertaining to the constraints developed in this article is formulated as follows:

$$\begin{cases} \text{rms}(f) \leq \frac{[fd]}{3} \\ \text{rms}(F) \leq \frac{[Fw]}{3} \\ \varphi \leq 6^\circ \\ \theta \leq 3^\circ \end{cases}. \quad (20)$$

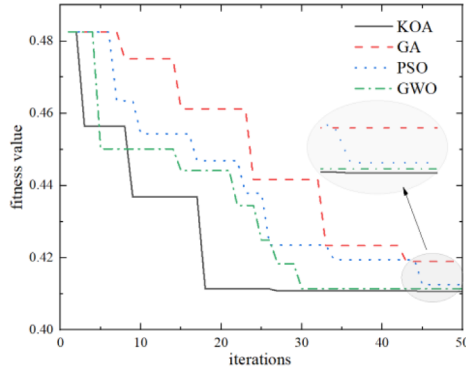


Fig. 6. Comparison of fitness curves for different algorithms.

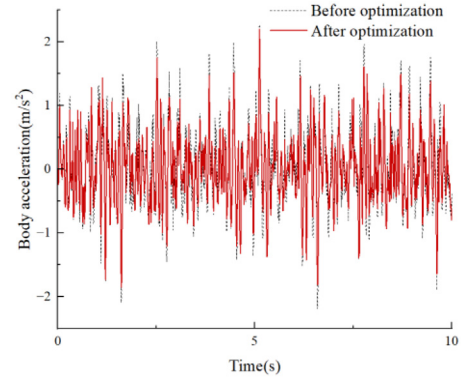
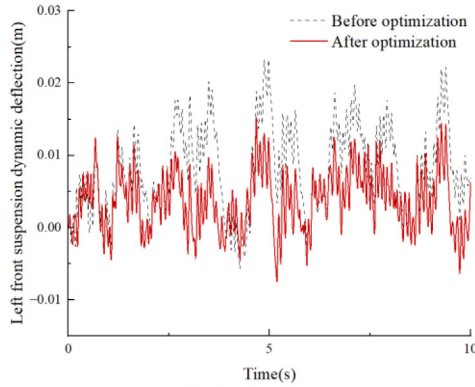
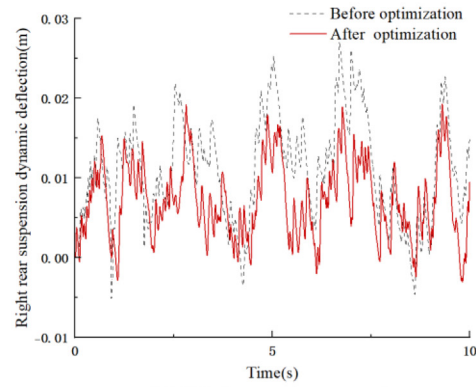


Fig. 7. Comparison of vehicle body acceleration.



(a) Left front suspension



(b) Right rear suspension

Fig. 8. Comparison of suspension dynamic deflection.

According to engineering experience, to reduce the probability of frequent collisions with limit blocks during vehicle operation, the dynamic deflection of the suspension should not exceed $1/3$ of the maximum limit travel of the suspension. Due to the self-weight of mining vehicles, to avoid excessive wheel dynamic loads on the road, the dynamic load on the wheel under constraint conditions must not exceed one-third of the vehicle's static load capacity. Due to the high center of mass and large inertia of the car, to avoid rollover and serious pitch of the mining vehicle, the vehicle's roll angle should be less than 6° and the pitch angle should be less than 3° based on the control stability.

4 Results

In the KOA, the population size is set at 20, and the maximum iterations number is fixed at 50, the T_c parameter to control global convergence is set to 3, the initial value of μ is set to 0.1, and the gamma parameter is set to 15. In addition, this article compares three other optimization algorithms, namely GA, PSO, and GWO [12,13]. The initial conditions are consistent with the KOA algorithm, the population size is set at 20, and the maximum iterations number is fixed at 50.

A comparison of the fitness function curves of different optimization algorithms is shown in Figure 6. This

optimization algorithm selects the objective function as the fitness function, and the convergence criterion is to minimize the objective function. The algorithm in Figure 6 will fall into a local trap after a certain number of iterations, that is, the local optimum, and then leave the local optimum after a certain number of iterations. This explains why the convergence curve shape shows gradient descent. The KOA optimization algorithm converges after 26 iterations, and the optimal fitness value is 0.4131. Compared with the GA, PSO and GWO algorithms, the KOA has better adaptability to complex nonlinear optimization problems, making the KOA significantly better than other algorithms in hydro-pneumatic suspension parameter matching performance, with the advantages of faster convergence, lower fitness values and faster removal from the local optimal value. The initial gas pressure of the front axle hydro-pneumatic spring p_a is 7 MPa, the initial gas volume V_a is 2.85 L, the damping orifice diameter D_a is 3 mm, the initial inflation pressure of the rear axle hydro-pneumatic spring p_a is 7.2 MPa, and the initial gas volume V_a is 2.31 L. The damping orifice diameter D_d is 3.69 mm.

A comparison of body acceleration before and after parameter matching is shown in Figure 7. A comparative analysis of the dynamic deflections between the left front wheel and the right rear wheel is presented in Figures 8a and 8b, respectively. Similarly, a comparative study of the dynamic loads exerted on the left front wheel and the right

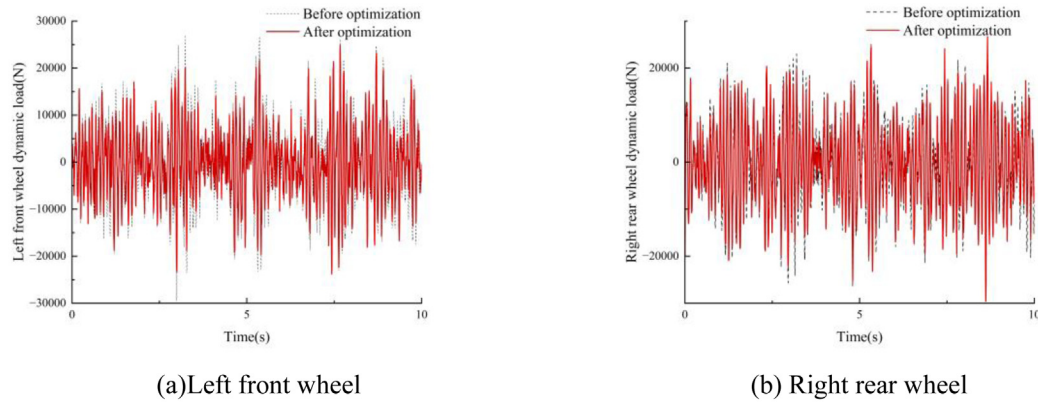


Fig. 9. Comparison of wheel dynamic loads.

Table 3. RMS values.

Index	Before optimization	Post optimization	Amount of improvement(%)
Body acceleration (m/s^2)	0.63	0.55	12.7
Dynamic deflection of the left front suspension (m)	0.01	0.0056	44
Dynamic deflection of the right front suspension (m)	0.013	0.0053	59.23
Dynamic deflection of the left rear suspension (m)	0.0126	0.0054	57.14
Dynamic deflection of the right rear suspension (m)	0.0128	0.0051	60.16
Dynamic load on the left front wheel (N)	8850	7715	12.82
Dynamic load on the right front wheel (N)	10498	8753	16.62
Dynamic load on the left rear wheel (N)	10179	9557	6.11
Dynamic load on the right rear wheel (N)	9294	9000	3.16

rear wheel is depicted in [Figures 9a](#) and [9b](#). [Table 3](#) presents the root-mean-square (RMS) value pairs of the performance indicators, comparing their states before and after the parameter matching.

As shown in the figure, after the Kepler optimization algorithm was used, the vertical acceleration of the vehicle body, the dynamic deflection of the suspension, and the dynamic load of the wheels were significantly reduced. Among them, the optimization effect of the dynamic deflection of the suspension was the best, greatly reducing the probability of the suspension hitting the limit block. The optimization of the vertical acceleration of the vehicle body addresses the driver's riding comfort and the degree of bumps. The reduction of the wheel dynamic load index improved the wheel's grip ability on the ground, thereby greatly improving the vehicle's handling stability. After overall optimization, all suspension indicators are improved, and the dynamic performance of the entire vehicle is enhanced.

5 Conclusion

After the KOA algorithm was applied to optimize the three structural parameters, namely damping hole diameter, initial pressure of accumulator gas, and volume, the smoothness indicators of the vehicle, encompassing vertical

acceleration, suspension dynamic deflection, and wheel dynamic load, were notably improved.

The KOA optimization algorithm reached convergence after 26 iterations, and the optimal fitness value based on the objective function was 0.4131. Compared with GA, PSO, and GWO algorithms, KOA has better adaptability to complex nonlinear optimization problems, making it significantly better than other algorithms in the matching performance of hydro-pneumatic suspension parameters. It has the advantages of fast convergence speed, low fitness value, and fast removal speed from local optimal values.

The refined structural parameters included: an initial air pressure of 7 MPa for the front axle hydro-pneumatic spring, an initial gas volume of 2.85 L, a damping hole diameter measuring 3 mm; whereas, for the rear axle hydro-pneumatic spring, the initial inflation pressure was set at 7.2 MPa, accompanied by an initial gas volume of 2.31 L, and a damping hole diameter of 3.69 mm.

Upon the completion of optimization, the vehicle suspension exhibited a notable dynamic deflection attenuation, amounting to approximately 55.13%, along with the body acceleration attenuation of 13.12%. Furthermore, the wheel load reduction ranged from a minimum of 3.16% for the right rear wheel to a maximum of 16.63% for the right front wheel. These enhancements significantly bolstered the suspension's ride comfort, thereby affirming the efficacy of the employed optimization algorithm. The

research findings hold significant potential to serve as a valuable reference for addressing parameter matching issues in hydro-pneumatic suspension systems.

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Conflicts of interest

The author hereby proclaims that there are no conflicts of interest pertaining to the content or conclusions presented in this work.

Data availability statement

Article data can be obtained from the corresponding author upon reasonable request.

Author contribution statement

Yuchang Liu wrote the manuscript and was responsible for the simulation work. Shuai Wang and Geqiang Li contributed to the data and formatting of the article. Bo Mao, Zhenle Dong and Donglin Li contributed to the formal analysis.

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