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*Retraction*

# Retracted: Research on Finite Element Structure of Vehicle Suspension Control Arm Based on Neural Network Sensing Control

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] Y. Zhu, W. Jiang, and R. Qi, "Research on Finite Element Structure of Vehicle Suspension Control Arm Based on Neural Network Sensing Control," *Journal of Sensors*, vol. 2022, Article ID 2897065, 7 pages, 2022.

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*Research Article*

# Research on Finite Element Structure of Vehicle Suspension Control Arm Based on Neural Network Sensing Control

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To improve the adaptive control of the neural network under the influence of vehicle suspension control, the neural network control method is proposed. The specific content of the method analyzes the nonlinear properties of vehicle suspensions, proposes neural network-based adaptive control strategies, and develops neural network-based nonlinear algorithms and neural identifiers. Genetic algorithms perform predictive control of rear suspension through a compensation network. The experimental results show that the model structure is order $n = m = 2$, the AN1 network node is 4-6-1, the AN2 network node is 5-4-1, the AN3 network node is 6-4-1, and the learning correction rate is $\alpha = 0.90$. In the actual simulation calculation, the number of nodes in the hidden layer of the network is increased, and the minimum number of nodes is chosen to determine the structure of the network, since the control effect obtained is not fundamentally changed. The suspension, which is controlled by the neural network's adaptive control, has a vibration-reducing effect and is more effective by increasing the control of the rear suspension. The neural network has been shown to be able to effectively control the vehicle's control arm.

## 1. Introduction

The increasing improvement of people's living standard has put forward new requirements for all walks of life. Especially in recent years, with the vigorous development of the service industry, people travel more and more frequently, which puts forward new requirements for the comfort and safety of vehicles. The suspension technology, which is closely related to the various performance of automobile, has been gradually recognized by people and paid great attention to. The traditional automobile suspension technology is mainly automotive, which makes the car in the process of driving not feel the actual situation of the road flexibly and timely adjust the speed and load; there are great safety risks. This traditional suspension technology restricts the longitudinal deepening development of automobile suspension systems to a certain extent. And with the further development of science and technology, economy, and society, this type of suspension system has no longer adapted to the needs of people's car performance. Therefore, it is of great practical significance to explore and study automobile suspension technology on a deeper level. The competition in the automobile industry is becoming more and more intense. In order to balance the high efficiency, high quality, and low cost development with product individuation, the major automobile enterprises are focusing on the engineering development technology of the vehicle architecture. As an important part of the framework, the influence of the framework bandwidth on the component design should be fully considered in the design stage to meet the requirements of shareability on the framework platform. In the development process of the rear suspension control software arm based on a specific building project, it is necessary to adopt multibody dynamics, finite element method (FEM), and other durability evaluation and structural optimization design technologies and combine with design and manufacturing experience. After the completion of software development, it is also necessary to use simulation tools to carry out durability analysis and structural optimization prediction and conduct a vehicle road test to complete durability verification, so as to realize the efficient and high-quality design and development of the construction project control software. The control arm (Control arlTl, also known as the swing arm), as the guiding and force transmission element of the automobile suspension system, transmits various forces acting on the wheels to the body and at the same time ensures that the wheels move according to a certain trajectory. The control arm elastically connects the wheel and the body together through ball joints or bushings, respectively. The control arm (including the bushing and ball joint connected to it) should have sufficient rigidity, strength, and service life.

In automotive suspension control software technology, the earliest control software method of active suspension control technology is canopy damper control software. Because of its simple control software algorithm, the canopy damper control method has been widely used in the automotive active suspension control technology as soon as it comes out. With the modern development of control theory, the stochastic optimal control software method of active suspension appears. The content and principle of this method are similar to the above control strategy of automobile suspension, so the author will not repeat it. With the development of recent years, Rizkin et al. proposed a neurofuzzy adaptive controller for vehicle suspension based on recursive neural network modeling. The neural network is used to identify the dynamic parameters of the vehicle suspension and provide learning signals for the neurofuzzy adaptive control software controller [1]. Rizvi et al. proposed a semiactive suspension system of automobile based on neural network adaptive control. Compared with automobile suspension, this semiactive suspension has the best damping performance [2]. Wu et al. proposed a fuzzy neural network method to design the vehicle height controller. According to the working principle of the vehicle height adjustment process, a mathematical model of the vehicle system was established based on vehicle system dynamics and the thermodynamic theory of variable mass charging and discharging gas systems [3]. Fuzzy theory and neural network promote the further development of vehicle structure and parameter identification. The development of modern computer technology, modern information and communication technology, and Internet technology makes it possible for intelligent control software of automobile suspension technology. And in the 1990s, the fuzzy control software method has been applied to the research of automobile suspension control. Because this control method can automatically adjust and combine the input variables and learn the parameters of membership function and the number of fuzzy rules, the simulation effect is much better than the conventional method. Therefore, this control method has been highly valued by automotive researchers and automobile manufacturers [4].

The control arm, also known as the swing arm, is an important safety and functional part of the automobile suspension system. In the design of the control arm, its strength, natural frequency, and longitudinal (front-rear direction of the car) and lateral (left-to-right direction of the car) stiffness should meet the specified requirements. The outer end of the control arm is connected to the wheel hub through a ball joint, and the inner end is connected to the vehicle body through a ball joint and a rubber bush. When establishing the finite element analysis model of the control arm topology optimization and performance calculation, in order to accurately reflect the influence of the spherical hinge and bushing on the control arm optimization results, the boundary conditions such as the spherical hinge and the bushing should be included. The vehicle suspension control arm system is a nonlinear system, and the conventional control strategy has some limitations when applied to the nonlinear system. In order to approach the actual system better and obtain a better control software effect, a better control strategy is needed. In recent years, the control software method using the neural network has been paid more and more attention. Because the neural network can approach arbitrary nonlinear functions and has the characteristics of adaptive learning, parallel distribution processing, strong robustness [5], fault tolerance, etc., it is suitable for modeling and control software of complex nonlinear systems such as automobile suspension. On the basis of current research, in order to improve the neural network adaptive control of the automotive suspension control software effect. The face to the neural network control method is put forward, the method analyzes the specific content of the nonlinear characteristic of automobile suspension, and the adaptive control strategy is proposed based on the neural network and designed a robust adaptive control software based on the neural network of nonlinear algorithm and neural controller and the use of genetic algorithm and through a compensating network, to rear suspension control. It is proved that the neural network can effectively control the vehicle suspension control arm.

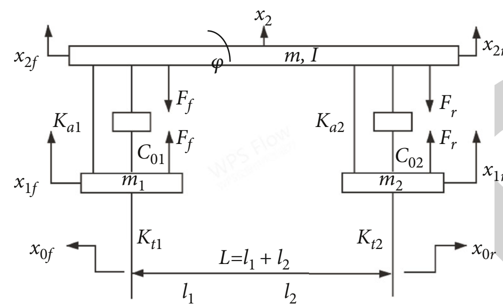


Figure 1: Controlled model of automobile suspension system: $m$: spring mass; $I$: the moment of inertia; $m_1, m_2$: front and rear axle unsprung mass; $x_{0f}, x_{0r}$: road roughness for front and rear wheel input; $x_{1f}, x_{1r}$: displacement of front and rear axle unsprung mass; $x_{2f}, x_{2r}$: body front and rear end displacement; $x_2$: displacement of sprung mass center of mass; $\phi$: angular displacement; $K_{a1}, K_{a2}$: front and rear suspension stiffness; $K_{t1}$, $K_{t2}$: stiffness of front and rear tires; $C_{01}, C_{02}$: front and rear shock absorber base value damping; $L$: the wheelbase; $l_1, l_2$: distance from center of mass to front and rear axis; $F_f, F_r$: control force required for front and rear suspension.

## 2. Experimental Methods

### 2.1. Establishment of Automobile Nonlinear Model

(1) Figure 1 shows a 4-DOF automobile membrane type equipped with automobile suspension

(2) Nonlinear processing of suspension

The spring and shock absorber in the suspension system are nonlinear components. The spring can be expressed as the following nonlinear function [6]:

$$F_S = K_S \operatorname{sgn}(\Delta x)|\Delta x|^n, \tag{1}$$

where $F_S$ is spring tension, $K_S$ is spring stiffness, $\Delta x$ is spring relative displacement, and $n$ is nonlinear exponent.

The nonlinear function of the shock absorber can be expressed as

$$F_d = C\Delta x \begin{cases} C = C_T, & \Delta \dot{x} > 0, \\ C = C_C, & \Delta \dot{x} < 0, \end{cases} \tag{2}$$

where $F_d$ is damping force and $C_t, C_c$ is damping values during stretching and compression.

(3) Mathematical model

The motion differential equation established is

$$\begin{cases} M\ddot{x}_2 + K_{s1} \operatorname{sgn}\left(\Delta x_f\right)\left|\Delta x_f\right|^n + F_f + C_{01}\Delta\dot{x}_f + K_{s2} \operatorname{sgn}(\Delta x_r)|\Delta x_r|^n + F_r + C_{02}\Delta\dot{x}_r = 0, \\ I\ddot{\phi} + b[K_{s2} \operatorname{sgn}(\Delta x_r)|\Delta x_r|^n + F_r + C_{02}\Delta\dot{x}_r] - a\left[K_{s1} \operatorname{sgn}\left(\Delta x_f\right)\left|\Delta x_f\right|^n + F_f + C_{01}\Delta\dot{x}_f\right] = 0, \\ m_1\ddot{x}_{1f} + K_{t1} \operatorname{sgn}\left(x_{1f} - x_{0f}\right)\left|x_{1f} - x_{0f}\right|^n - \left[K_{s1} \operatorname{sgn}\left(\Delta x_f\right)\left|\Delta x_f\right|^n + F_f + C_{01}\Delta\dot{x}_f\right] = 0, \\ m_2\ddot{x}_{1f} + K_{t2} \operatorname{sgn}(x_{1r} - x_{0r})|x_{1r} - x_{0r}|^n - [K_{s2} \operatorname{sgn}(\Delta x_r)|\Delta x_r|^n + F_r + C_{02}\Delta\dot{x}_r] = 0, \end{cases} \tag{3}$$

where

$$\begin{aligned} \Delta x_f &= x_{2f} - x_{1f}, \\ \Delta x_r &= x_{2r} - x_{1r}, \\ x_2 &= \frac{ax_{2r} + bx_{2f}}{a+b}, \\ \phi \approx \tan\phi &= \frac{x_{2r} - x_{2f}}{a+b}, \\ F_{d1} &= C_{01}\Delta\dot{x}_f \begin{cases} C_{01} = C_{t01}, & \Delta\dot{x}_f > 0, \\ C_{01} = C_{c01}, & \Delta\dot{x}_f < 0, \end{cases} \\ F_{d2} &= C_{02}\Delta\dot{x}_r \begin{cases} C_{02} = C_{t02}, & \Delta\dot{x}_r > 0, \\ C_{02} = C_{c02}, & \Delta\dot{x}_r < 0. \end{cases} \end{aligned} \tag{4}$$

Since the human body's response to vibration is mainly evaluated by vibration acceleration, in order to improve the ride comfort of the vehicle, the vibration acceleration should be reduced as much as possible [7]. Therefore, the vertical acceleration at the center of mass of sprung mass is taken as the output variable of the system; that is, $y = \ddot{x}_2$ is set as the control force required by front and rear suspension with the following relation $F_r = F_f(t_0 - t_d)$, where $t_0$ is the current moment, $t_d$ is the time lag $t_d = L/v$, and $v$ is the speed of the car.

Thus, the control input force of the suspension system is $F_f$, and the model parameters are shown in Table 1.

*2.2. Adaptive Control of Nonlinear Neural Network.* It can be seen from Table 1 that the model includes the spherical hinge and bushing connected to it. Under the action of external load, the control arm will have a large displacement.

A three-layer BP neural network AN1 is used for online identification of the controlled object, and another three-layer BP neural network AN2 component is used. Suppose that the automobile suspension system is a single input and single output nonlinear system, which can be described as

$$y(k) = f[y(k-1), \cdots, y(k-n), u(k-1), \cdots, u(k-m)], \tag{5}$$

where $y, u$ is the output and input of the suspension system representing the vertical vibration acceleration $\ddot{x}_2$ and control software force $F_f$ at the center of mass of sprung mass of order of time series $\{y(k)\}$ and $\{u(k)\}$ and $f[\cdot]$ is the nonlinear function.

Let the neural network model used to identify object features be the following.

The input layer

$$O_i^1(k) = \begin{cases} y(k-i), \ 0 \le i \le n-1, \\ u(k-i+n), & 0 \le i \le n+m-1. \end{cases} \tag{6}$$

Hidden layer

$$\begin{aligned} \text{net}_i(k) &= \sum_i v_{ij} O_j^1(k), \\ O_j^2(k) &= a[\text{net}_i(k)], \end{aligned} \tag{7}$$

where $\{v_{ij}\}$ is weights and $a(x)$ is the excitation function, take

$$a(x) = \frac{1}{1 + \exp(-x)}. \tag{8}$$

Table 1: Model parameters.

| Sprung mass | The moment of inertia | Front axle unsprung mass | Rear axle unsprung mass | Distance from center of mass to front axis | Distance from center of mass to rear axis | Front suspension stiffness | Rear suspension stiffness |
|---|---|---|---|---|---|---|---|
| 505 | 731 | 32.5 | 49.5 | 1.09 | 1.46 | 9 | 11 |
| Tensile damping value of the front shock absorber | The front shock absorber pulls the compression value | Front tire stiffness | Rear tire stiffness | Tensile damping value of rear shock absorber | The rear shock absorber pulls the compression value | | |
| 2440 | 580 | 160000 | 160000 | 2500 | 650 | | |

The input layer $\hat{y}(k+1)=\sum_i w_i O_i^2(k)$, where $\hat{y}$ is the output of neural network AN1 and $\{w_i\}$is weights.

If the performance indicators

$$J_m=\frac{1}{2}[y(k+1)-\hat{y}(k+1)]^2. \tag{9}$$

For minimization, the following weight coefficient learning rule can be obtained:

$$\begin{gathered}\Delta w_i(k)=a[y(k+1)-\hat{y}(k+1)]O_i^2(k),\\ \Delta w_i(k)=a[y(k+1)-\hat{y}(k+1)]a[\mathrm{net}_i(k)]w_i(k)O_j^1(k),\end{gathered} \tag{10}$$

where $a$ is the learning correction rate, $0<a\le 1$.

In the neural network controller, its adaptive parameter is the weight coefficient of the neural network. After proper learning, it can control objects with unknown characteristics and adapt to the changes in the environment. The design of the neural network controller makes full use of the information of the identifier [8]. Its form is the same as that of the identifier, and its performance index is

$$J_c=\frac{1}{2}[y^*(k+1)-\hat{y}(k+1)]^2, \tag{11}$$

where $y^*$ is the desired output and $\hat{y}$ is the estimated output.

After proper learning, $\hat{y}$ will approach $y$, so

$$J_p=\frac{1}{2}[y^*(k+1)-y(k+1)]^2 \tag{12}$$

can be replaced by the minimization of equation (11). The correction of controller weight still uses the BP algorithm, the same as above.

*2.3. Rear Suspension Foresight Control.* It is easy to take the road surface information obtained by the front wheel as the predictive information of the rear suspension control if the rear wheel drives along the track passed by the front wheel. This control method is called the predictive control software of the rear suspension. For predictive control, it is to pay attention not only to the past and present target values but also to the future target values, so that the deviation between the target value and the controlled quantity is minimized as a whole. Obviously, the predicted time is $L/v$, and the symbolic meaning is the same as before. Different from the previous control strategy, a three-layer rear suspension compensation network AN3 is added, which can make use of the road surface information obtained by the front wheels to make certain compensation for the rear suspension control in advance, and the compensation value is $\Delta u$.

Make

$$p(k)=[w(k-1),\cdots,w(k-d)], \tag{13}$$

where $w(k)$ is road interference signals experienced by the front wheels of a car, $p(k)$ is the road interference signal at each sampling moment between front wheel and rear wheel, and $d$ is the amount of lag.

At time $k$, the input of the network is

$$O_i^1(k)=\{y^*(k),y(k-1),\cdots,y(k-n),u(k-1),\cdots,u(k-m),p(k)\}. \tag{14}$$

*2.4. Genetic Algorithm Neural Network Control Strategy.* The combination of neural network and genetic algorithm can be a scientific method of searching optimal operation. For a 1/2 vehicle suspension model, weight coefficient of index, sprung mass, and suspension stiffness have important influence on the stability of the system. Considering the vehicle riding comfort and handling stability, dynamic load of the sprung mass acceleration, wheels, and the suspension dynamic deflection as an important index to evaluate the active suspension control results and control objective function is selected:

$$\begin{aligned}J=&\rho_1\ddot{z}_2^2+\rho_2\ddot{\varphi}_2^2+\rho_3\frac{y_f^2+y_r^2}{2}\\&+\rho_4\frac{(z_{1f}-z_{0f})^2+(z_{1r}-z_{0f})^2}{2}+\rho_5u_f^2+\rho_5u_r^2.\end{aligned} \tag{15}$$

Among them, $y_f=z_2+a^{\varphi}-z_{1f}y_r=z_2-b^{\varphi}-z_{1r}$ inverse of the objective function was selected as the fitness function. The weight coefficient $\rho_1\sim\rho_6$ in the fitness function was optimized by a genetic algorithm. This quadratic objective function is a comprehensive performance index to evaluate the output of suspension. If the value of $J$ decreases to a certain extent, it indicates that the vehicle performance has been better coordinated and integrated. The population size of the genetic algorithm was selected as 45 [fixed], end evolution algebra (100). If the crossover probability is too high, the good pattern will be destroyed, and if the crossover probability is too small, the speed of new individuals will be reduced, and the crossover probability is 015. If the mutation probability is too high, the excellent model will be destroyed; if the mutation probability is too small, the ability to inhibit precocity will be poor, and the mutation probability is 0.1. The neural network system adopts the structure of the double hidden layer, and the weight coefficient learning law in the learning algorithm adopts the improved algorithm combining the learning rate self-adaptive adjustment and momentum term, namely,

$$w_{ij}(t+1) = w_{ij}(t) - \eta(t)\sum_{p}\delta_{m1p} + a\Delta w_{ij}(t), \qquad (16)$$

where $\eta$ is the learning rate coefficient and $a$ is the momentum coefficient.

The momentum term makes the adjustment change towards the average direction at the bottom of the error surface, which plays the role of buffering smoothing and accelerates the learning rate. The neural network is used to simulate the dynamic response of the system, and the genetic algorithm is used to optimize and adjust the weight of the network, so that the dynamic response of the suspension system can achieve the expected effect.

## 3. Simulation Experiment Results and Analysis

MATLAB+Simulink+Toolbox software was used for the simulation study [9]. The four-order Runge-Kutta method was adopted for simulation, and the step size of the system simulation was 0.01. Assume that the car drives on the C-class road at a speed of $v = 20\,\mathrm{m/s}$, the road roughness coefficient $G_q(n_0) = 256 * 10^{-6}\,\mathrm{m}^2 \cdot \mathrm{m}^{-1}$, and the variance of the road random excitation signal $\sigma^2 = 0.101\,\mathrm{m}^2/\mathrm{s}^2$. The model structure is as follows: order $n = m = 2$, the AN1 network node is 4-6-1, the AN2 network node is 5-4-1, the AN3 network node is 6-4-1, and the learning correction rate is $a = 0.90$. In the actual simulation calculation, the control effect obtained by adding hidden layer nodes is basically unchanged. Therefore, the minimum number of nodes is selected when determining the network structure. Some parameters used in the simulation calculation are shown in Table 1, and the simulation results are shown in Figures 2–5. Figure 2 is the simulation curve of the vertical vibration acceleration response of the automobile suspension body. Figure 3 shows the vibration acceleration curve of vehicle suspension controlled by the neural network. Figure 4 shows the control force curve of the predictive control software vehicle suspension, and Figure 5 shows the vibration response of the predictive control vehicle suspension vehicle with the neural network. It can be seen from the figure that the vibration reduction effect of automobile suspension controlled by the neural network is better, while the control software effect of the automobile suspension system with forethought control on vehicle body vibration is further improved, and the control energy is smaller.

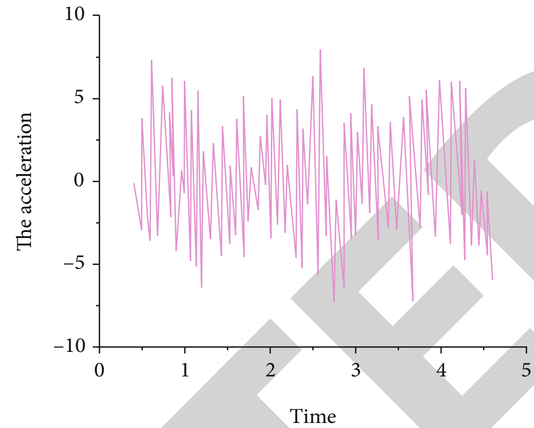


Figure 2: Vertical acceleration response of vehicle body with trigger frame.

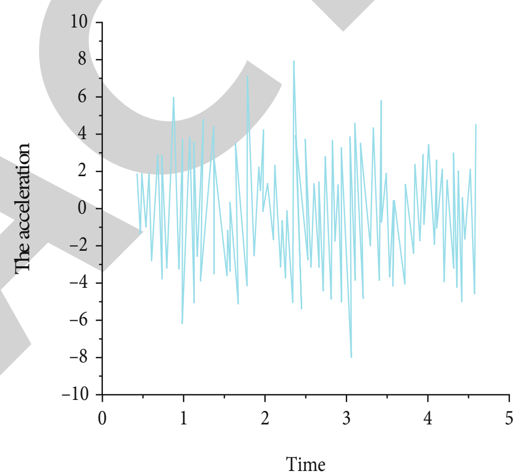


Figure 3: Neural network adaptive control of vehicle body vertical acceleration response.

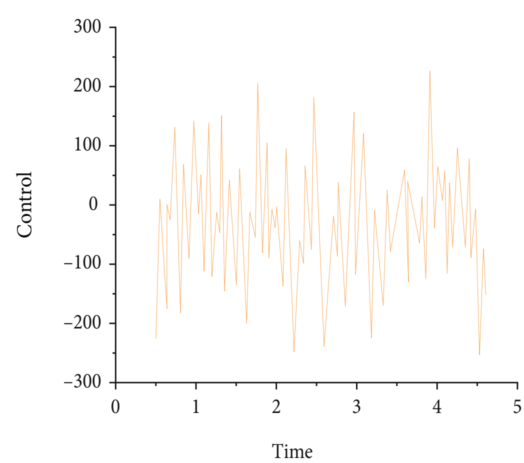


Figure 4: Shows the control force of the vehicle suspension.

It can be seen from the simulation results that, compared with the automobile suspension, when the road input is random input, the acceleration of the active suspension and the standard deviation of the suspension dynamic travel both

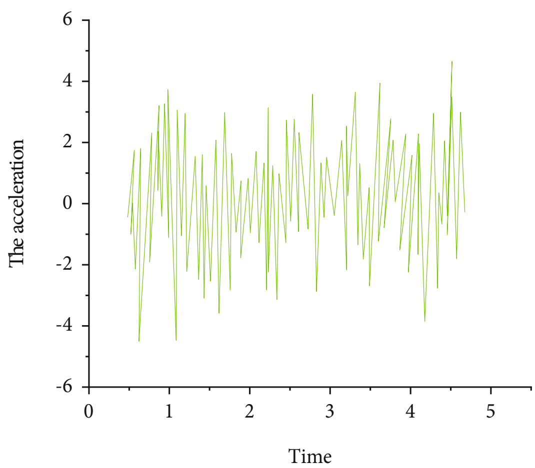


Figure 5: Predicts the vertical acceleration response of the control vehicle body.

decrease to a certain extent, while the standard deviation of the wheel dynamic load increases to a certain extent. The designed controller [10], whose rules are learned by a neural network genetic algorithm, is very effective for reducing suspension acceleration and suspension dynamic travel. The existing problems are as follows: while the acceleration of the car body and the dynamic deflection of the suspension are improved, the dynamic deformation of the wheel is worsened. There is an inherent contradiction between acceleration and dynamic deformation in suspension control software. By changing the control parameters, the influence of vehicle body acceleration and wheel dynamic deformation is studied.

(1) The road condition is changed from Grade C road surface to Grade B road surface. The root mean square value of acceleration on B class road surface is 11618 m/s, and the root mean square value of dynamic deformation of front wheels is 0102428 m. RMS of body acceleration on C class road surface is 31099 m/s, and RMS of front wheel dynamic deformation is 0102295 m

(2) When the vehicle speed was changed to 30 m/s, the vertical acceleration of the vehicle body and the dynamic deformation of the front wheel did not change compared with the vehicle speed of 20 m/s, as you can see

(3) The body vertical acceleration and the front wheel dynamic deformation response are only limited by the algorithm. In this algorithm, the speed change does not affect the simulation results

(4) (a) When the number of individuals in the initial population is changed to a small population, the calculation speed can be improved, but the population diversity can be reduced, so the optimal solution may not be found. When the population is large, the search range is wide, the calculation amount of individual fitness evaluation is increased, and the convergence speed is reduced. (b) The suspension performance is obtained by changing the type of the crossover function xOverFNs in the input parameter to heuristicXover. (c) MultiNonUnifMutation was changed from nonUnifMutation to multiNonUnifMutation in the input parameters, and the suspension performance was obtained by changing the parameters. The simulation results are obtained by changing the parameters in the genetic algorithm. Vehicle body acceleration and angular acceleration are effectively controlled [11]. And after changing the control parameters, the dynamic deformation of the tire is also reduced accordingly, which improves the comprehensive performance of the suspension

The results show that the suspension control software method based on the genetic algorithm neural network has a significant effect on improving vehicle ride comfort. In order to check the actual working effect of the automobile suspension, the self-developed automobile suspension is put on the electrohydraulic vibration test bench, and the vibration test is carried out. The system is mainly composed of the acceleration sensor, charge amplifier, single chip microcomputer, adjustable damper, stepping motor, and driving power supply. By collecting acceleration signals of sprung mass and according to the neural network control strategy, the corresponding control signals are given to drive the stepping motor to rotate and adjust the damper to the optimal value, so as to achieve the ideal vibration reduction effect. During the test, the acceleration excitation signals recorded in advance at the axle when the car runs on different road surfaces are played back by a tape machine, so that the excitation signals are reproduced on the shaker of the test bench. For convenience of comparison, the vibration test of automobile suspension is also done. In summary, the intelligent control function of the neural network can significantly reduce the vibration acceleration of the car and improve the comfort of the seat.

The simulation results show that the controller designed in this paper is effective in reducing the acceleration of the vehicle body, the acceleration of the pitch angle, and the dynamic travel of the suspension. The problem is that while the body acceleration and the dynamic travel of the suspension are improved, the dynamic load of the wheel is deteriorated. By trying to change the control parameters, such as learning rate, maximum training times, target error, network structure, initial population number of individuals, type of crossfunction, and type of variation function, the system response characteristics are changed, and the dynamic load of the tire is also reduced, so that the comprehensive performance of the suspension can be improved. It shows that the suspension control method based on the genetic algorithm neural network has a significant effect on improving vehicle ride comfort, and the proposed control method has a good adaptability to the established active suspension model [12].

## 4. Conclusions

This paper presents a method for neural network control. The study found that the vibration reduction effect of the automobile suspension controlled by the neural network is better, and the control effect of the automobile suspension system with predictive control on the body vibration is further improved, and the required control energy is small. To prove the effect of this method in solving the problem of the vehicle suspension control arm controlled by the neural network, it is embodied in that it is effective in reducing the body acceleration, the pitch angle acceleration, and the suspension dynamic stroke. The problem is that while the acceleration of the body and the dynamic travel of the suspension are improved, the dynamic wheel load is deteriorated. By trying to change the control parameters, such as changing the learning rate, the maximum number of training times, the target error, the network structure, the number of individuals in the initial population, the type of crossover function, and the type of variogram, the system response characteristics have changed, and the dynamic load of the tire has also been reduced accordingly, so that the overall performance of the suspension can be improved.

The thinking used in the fine research on automobile suspension technology is modeling thought, and the method used is combining the linear and nonlinear characteristics of suspension control technology. With the continuous improvement of people's requirements for automobile comfort and safety performance, the research on automobile suspension control technology still needs to be further in-depth. In actual automobile manufacturing, linear matrix calculation should be combined to choose the most suitable method to carry out production operations, so as to continuously meet people's needs for automobile performance.

The technological innovation of suspension technology is closely related to the development of related disciplines, advanced computer technology, automatic control technology, fuzzy control, and neural network. Advanced manufacturing technology, motion simulation, etc., provide a strong guarantee for the further development of suspension. At the same time, the development of suspension also puts forward higher theoretical requirements for these related disciplines. The two complement each other and promote each other, so as to achieve real sustainable development.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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