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Design of Vehicle Structural Stability and Safety Control System Based on Genetic Algorithm

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In the field of vehicle structural stability and safety control, traditional optimization methods lack sufficient global search capability and flexibility, making it difficult to simultaneously consider the conflicts and nonlinear relationships between various objectives in complex and multi-objective dynamic environments. In response to these issues, this study used a control system design method based on the improved SPEA2 (Strength Pareto Evolutionary Algorithm 2) to optimize suspension system parameters and power allocation strategies through a combination of elite strategy and Pareto ranking. By constructing a multi-objective optimization model, suspension stiffness, body inclination angle, and power distribution ratio were used as optimization variables, and then a dynamic weight update mechanism was introduced to address target conflicts under complex operating conditions. The experimental results showed the method proposed in this study controlled the yaw rate of the vehicle within 1.4 rad/s during sharp turns, reduced the wheel slip rate to 6.0% on slippery roads, and shortened the power response time to 2.4 seconds. This method effectively improves the dynamic performance of vehicles in complex environments, strengthening the robustness of the system and enhancing its adaptability.

Keywords: genetic algorithm optimization, vehicle stability control, safety control system, multi-objective optimization, pareto-based ranking, suspension system design

1. INTRODUCTION

The vehicle industry is developing rapidly, with the current focus being on the performance and driving safety of vehicles. With the increasing trend of intelligence [1–2] and electrification [3], the structural stability and safety control system of vehicles [4–5] needs to meet higher performance requirements in order to cope with complex road conditions, dynamic working conditions, and changing environments. To ensure the driving safety and handling stability of vehicles under various harsh conditions [6–7], researchers have proposed various control strategies such as PID (Proportional-Integral-Derivative)-based [8] vehicle dynamic stability control, fuzzy logic control [9–10], and Model Predictive Control (MPC) [11]. Although PID control design is simple and performs well in single objective optimization [12], it lacks sufficient flexibility and adaptability in multi-objective coupling problems, is prone to control failure due to the coupling effects of multiple variables, and has obvious limitations when facing complex nonlinear systems. Fuzzy logic control is a method of handling uncertain factors by introducing expert experience, which has been applied in the joint control of suspension systems [13–14] and power allocation. However, due to the dependence of fuzzy rule design on prior knowledge, it often exhibits response lag and insufficient stability when encountering highly dynamic and complex working conditions. MPC achieves high control accuracy theoretically by rolling and optimizing the prediction model at each moment, taking into account the target changes in the future period of time. However, the MPC method requires a large amount of real-time computation, so it is difficult to meet the real-time requirements of actual vehicle environments. The limitations

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of traditional methods are particularly evident in the face of complex problems such as multi-objective conflicts, dynamic adaptability, and global optimization. When the vehicle is driving on difficult terrain such as mountains, slippery roads, and rough roads [15], the stiffness of the suspension system, body posture, and power distribution strategy often exhibit a strong coupling relationship. Existing methods cannot effectively coordinate the balance between various objectives, resulting in a decrease in the overall control performance of the vehicle. People now need to design a control strategy that achieves global optimization, multi-objective balance, high real-time performance, and robustness under complex working conditions, in order to solve key problems in the field of vehicle structural stability and safety control.

To address the above challenges, this study proposes a multi-objective optimization control method based on an improved SPEA2 algorithm applied to the global optimization design of vehicle suspension systems and power distribution strategies. SPEA2, as a multi-objective evolutionary algorithm, has stronger global search capabilities in maintaining population diversity and multi-objective balance by introducing state-of-the-art strategies and a selection mechanism based on Pareto sorting. To implement the method proposed in this paper, a multi-objective optimization model for the vehicle suspension system and power distribution was first established, with suspension stiffness, body inclination angle, and power distribution ratio as the core optimization variables. The multi-objective optimization control was carried out using the SPEA2 algorithm. To avoid premature convergence and local optimal solutions in complex multi-objective optimization problems using traditional genetic algorithms, this study adopted a start-of the-art strategy to retain high-quality solutions in each generation of the population, preserve the global optimal solutions and the balance of population diversity through population screening and Pareto sorting. Through simulation verification under different complex working conditions, the test scenarios cover various typical working conditions such as sharp turns, uphill driving, and slippery roads. The proposed method demonstrates excellent stability and dynamic response performance in all test scenarios. Compared to traditional methods, the optimization strategy based on SPEA2 effectively improves the overall dynamic performance of the vehicle. The multi-objective optimization strategy based on SPEA2 algorithm improves the overall performance of vehicle suspension system and power distribution control through dynamic weight update mechanism, providing effective technical support and a sound theoretical basis for the design of structural stability and safety control system of future intelligent vehicles.

2. RELATED WORK

Nowadays, many studies have focused on improving the driving safety and handling stability of vehicles in various difficult road conditions and dynamic working environments. These studies cover different control methods and optimization techniques, providing rich theoretical basis and practical experience for solving key problems in the current field. Zhu et al. [16] used the Reverse Labeling Dijkstra Algorithm (RLDA) [17] to solve the vehicle path planning problem taking into account the features of intersections, constructed a mathematical model, and verified the effectiveness of the algorithm through simulation experiments. Recent advances in vehicle path planning have incorporated intersection optimization techniques, as demonstrated in studies on urban logistics and dynamic routing challenges [18–19]. Chen et al. [20] proposed a novel control strategy for autonomous vehicles equipped with front and rear independent steering systems [21]. They improved the obstacle avoidance capabilities through path replanning, path tracking, and stability control [22–23], and improved path tracking and handling stability under extreme operations. The real-time effectiveness was verified in the hardware in the loop simulation environment, and the obstacle avoidance function was validated in the preset obstacle scene. Zhang, Jie et al. [24] proposed a robust Adaptive Sliding Mode (ASM) controller [25–26] for improving the handling and lateral stability of steer by wire vehicles. By using a sliding mode state observer to estimate the vehicle's sideslip angle, an ASM lateral stability controller was designed to calculate the corrected steering angle, and the target steering angle was achieved through a low-level ASM steering controller. The hardware in the loop simulation results show that the controller exhibits excellent stability control performance under different steering operations.

In their study of vehicle safety and stability, Elhefnawy [27] and others [28–29] used fuzzy logic control combined with a genetic algorithm to develop a coordinated control system that includes direct yaw control and active front wheel steering. The system optimized vehicle handling, cornering stability, and anti-rollover performance and, through benchmark tests under different driving conditions, its ability to improve vehicle stability significantly was verified. Wu, Zheng et al. [30] studied the vehicle lateral electronic stability control algorithm by combining the BP neural network (Back Propagation Neural Network) with the PID control algorithm. They verified through joint simulation with MATLAB Simulink and CarSim, that the algorithm can automatically adjust control parameters, optimize the control process, and improve the stability of vehicles under different road conditions and vehicle speeds, which has high practical value.

Although significant progress has been made in the field of vehicle stability and safety control, most methods still have slow convergence speed, poor real-time performance, and unsatisfactory multi-objective optimization effects in complex dynamic environments. Therefore, this study implements multi-objective optimization control based on the improved SPEA2 algorithm, thereby improving the system's global search ability and real-time response ability under different operating conditions by introducing dynamic weight adjustment mechanism and a start-of-the-art strategy.

3. DESIGN AND OPTIMIZATION OF MULTI-OBJECTIVE OPTIMIZATION MODELS

3.1 Data Collection and Processing

The data in this study was derived from the vehicle dynamic performance testing platform, which conducted a

Table 1 Description of data sampling variables.

Variable Name	Measurement Location	Unit	Sampling Frequency
Suspension Stiffness	Front Axle, Rear Axle	N/m	100 Hz
Vehicle Body Inclination	Vehicle Center	Degree (°)	50 Hz
Wheel Slip Ratio	Front and Rear Drive Wheels	%	20 Hz
Power Distribution Ratio	Front and Rear Power Train	Dimensionless	30 Hz

Table 2 Statistics of data missing and denoising processing.

Condition Type	Total Sampling Points	Missing Points	Abnormal Points	Valid Points After Processing
Sharp Turn	5000	200	150	4650
Slope Start	4000	100	80	3820
Slippery Road Driving	3500	50	70	3380

Table 3 Input feature matrix of multi-objective optimization model.

Feature Variable	Description	Original Dimension	Dimension After Reduction
Suspension Stiffness	Stiffness changes under different conditions	100	20
Vehicle Body Response	Dynamic response characteristics during sharp turns	50	10
Power Distribution Ratio	Power distribution ratio characteristics	30	5
Wheel Slip Ratio	Wheel slip characteristics on slippery roads	40	8

large number of testing experiments under various difficult working conditions. The system collected data on multiple key variables, including suspension system stiffness, body posture, vehicle power response, and wheel slip rate. To ensure the integrity and accuracy of data collection, high-precision sensors and onboard data recording systems were used to monitor and record the real-time status of vehicles. The sensor network was distributed in various key parts of the vehicle, such as the suspension system, chassis, and power transmission system, to monitor real-time changes in suspension system stiffness, vehicle body inclination, wheel slip rate, and power distribution ratio under different working conditions. The sampling variables and their measurement positions, units, sampling frequencies, and other information are shown in Table 1.

The collected data was cleaned and denoised. Due to the presence of noise interference and data loss in complex operating conditions, this study used the Kalman Filter algorithm to smooth the data and eliminate instantaneous noise and outliers, thereby ensuring the stability and accuracy of the data. For missing sampling points, bilinear interpolation was used to estimate and fill in the missing data in order to obtain a complete data sequence. To further improve data quality, mean normalization was applied to eliminate dimensional differences between different variables, ensuring equal importance of each variable in the model input. Table 2 shows the missing data under different operating conditions and the comparison of the processed data volume.

In order to facilitate the construction and training of subsequent models, this study mapped the collected multidimensional data onto a unified timeline, and used time series analysis methods to align the variables in time series to ensure consistency in sampling frequencies for different data. The following formula was used for time series alignment:

$$Y(t) = \sum_{i=1}^{N} w_i X_i(t + \Delta t_i) \tag{1}$$

$Y(t)$ is the aligned data, X_i is the data sequence with different sampling frequencies, w_i is the weight factor, and Δt_i is the time offset.

In the data processing stage, the dynamic window segmentation algorithm was used to divide the data into multiple subsets based on the performance differences of vehicles under different road conditions. Each subset corresponds to specific operating conditions such as sharp turns, starting on slopes, and driving on wet roads. The data was split using the following formula:

$$D_{sub}(t) = \begin{cases} 1, \theta(t) > \theta_{threshold} \\ 0, \theta(t) \leq \theta_{threshold} \end{cases} \tag{2}$$

$\theta(t)$ represents the body inclination angle, and $\theta_{threshold}$ is the set threshold.

After completing data segmentation, principal component analysis (PCA) is used to reduce the dimensionality of the data, preserve the correlation between key variables, and calculate principal components through matrix decomposition. The mathematical expression for PCA dimensionality reduction is as follows:

$$Z = XW \tag{3}$$

Z is the reduced dimensional feature matrix, X is the original data matrix, and W is the projection matrix of PCA. The key features after dimensionality reduction and feature extraction are shown in Table 3.

3.2 Construction of Multi-Objective Optimization Model

The multi-objective optimization model needs to be based on mathematical models of vehicle suspension system parameters, body posture, and power allocation strategies, using target weight factors to balance the priority of each target under different dynamic operating conditions. The suspension stiffness affects the dynamic response of the vehicle body, the vehicle posture reflects stability and anti-slip ability, and the power distribution strategy determines the power transmission ratio between the front and rear axles and the left and right wheels. The combination of the three creates a multi-objective optimization problem.

The stiffness parameters of the suspension system are represented by the spring stiffness coefficient k_s and damping coefficient c_s. The spring stiffness coefficient is defined as:

$$F_k = k_s \cdot x_s \tag{4}$$

F_k is the restoring force generated by the suspension spring, and x_s is the amount of suspension deformation. The effect of damping coefficient is reflected in the damping force F_c of the shock absorber, and its mathematical expression is:

$$F_c = c_s \cdot \dot{x}_s \tag{5}$$

$\dot{x}_s$ is the speed response of the suspension system.

The vehicle attitude control model can be described by the pitch angle, roll angle, and yaw angle of the vehicle. The roll angle θ_r of the vehicle during turning is related to the vehicle speed v and steering angle δ as follows:

$$\theta_r = \arctan\left(\frac{v^2 \cdot \delta}{g \cdot L}\right) \tag{6}$$

g is the constant of gravitational acceleration, and L is the wheelbase of the vehicle. The calculation of yaw rate $\dot{\theta}_y$ is related to the vehicle's moment of inertia I_z and yaw moment H_y:

$$\dot{\theta}_y = \frac{H_y}{I_z} \tag{7}$$

By adjusting the body posture control parameters under different working conditions, the stability of the vehicle can be improved.

Regarding the power distribution strategy, the power distribution ratio α between the front and rear axles and the distribution ratio β between the left and right wheels are key factors in optimizing control. The power allocation ratio model is:

$$\alpha = \frac{M_f}{M_f + M_b} \tag{8}$$

$$\beta = \frac{M_l}{M_l + M_r} \tag{9}$$

M_f and M_b represent the driving torque of the front and rear axles respectively, while M_l and M_r represent the driving torque of the left and right wheels. This model ensures balanced power output under different operating conditions, thereby improving the vehicle's driving stability and anti-slip ability.

Based on the suspension system parameters, vehicle posture, and power allocation strategy mentioned above, this study transformed it into a multi-objective optimization problem. In order to achieve global optimization of vehicle performance under complex dynamic conditions, it was necessary to introduce weight factors w_1, w_2, and w_3 for different objectives, corresponding to the importance of suspension stiffness, body posture, and power allocation strategy in the objective function. The objective function of the multi-objective optimization problem is:

$$minf(x) = w_1 \cdot f_1(k_s, c_s) + w_2 \cdot f_2(\theta_p, \theta_r, \theta_y) + w_3 \cdot f_3(\alpha, \beta) \tag{10}$$

$f_1(k_s, c_s)$ is the optimization objective of suspension system parameters, taking into account the dynamic response time and shock absorption effect of the vehicle body; $f_2(\theta_p, \theta_r, \theta_y)$ reflects the stability of the vehicle's posture during sharp turns, uphill driving, and high-speed driving; $f_3(\alpha, \beta)$ is the optimization objective of power allocation strategy, aimed at reducing vehicle sideslip rate and improving power response time.

This study proposes a dynamic weight update mechanism that can adapt to different complex working conditions. In complex terrain or sharp turning conditions, the weight factors of suspension stiffness and vehicle posture should be increased. When starting on a slope or driving on a slippery road surface, the weight of the power distribution strategy should be increased. The update of dynamic weights is adjusted based on the current state of the vehicle and external environmental parameters, specifically represented as:

$$w_i = w_i^0 \cdot (1 + \gamma \cdot E) \tag{11}$$

w_i^0 is the initial weight value of each objective, γ is the environmental response coefficient, and E is the environmental factor.

By constructing a multi-objective optimization model and dynamically adjusting weight factors, the robustness and balance of suspension system parameters, body posture, and power allocation strategy were ensured under different operating conditions.

3.3 Design of Improved SPEA2 Algorithm

In the design of the improved SPEA2 algorithm, population initialization ensures population diversity by generating individuals in the problem space. The calculation of the objective function adjusts the weights based on the objectives of the optimization model to balance different optimization requirements. The dynamic weight mechanism adjusts in real-time based on changes in the external environment and vehicle status, continuously optimizing the priority of each objective under complex working conditions, thereby achieving global optimization. The preservation of Pareto frontier solutions ensures the retention of the optimal solution in the population through an elite strategy (i.e., elitism, which retains high-quality individuals across generations), thereby avoiding the problem of local optima.

The combination of dynamic weight updating and other state-of-the-art strategies (such as Pareto-based ranking and adaptive selection mechanisms) further improves the adaptability of the algorithm, but also ensures effective prevention of premature convergence in multi-objective optimization. On

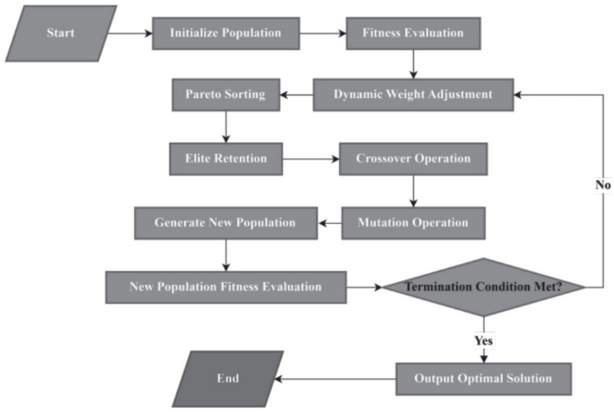

Figure 1 Optimization process.

this basis, the SPEA2 algorithm ensures the robustness and global optimality of the optimization results by introducing global search and elite retention mechanisms, and enables the algorithm to maintain efficient optimization performance even under difficult and changing working conditions.

3.4 Optimization Process and Algorithm Implementation

The optimization process for improving the SPEA2 algorithm is shown in Figure 1.

The initial population is distributed throughout the search space through random generation, ensuring sufficient diversity of the population. This diversity is particularly important for preventing algorithms from becoming stuck in local optima. Every individual in the population needs to undergo fitness assessment. The calculation of fitness value is based on the definition of objective function, where multiple objective functions are weighted and summed to obtain the total fitness value of the individual. In this process, the dynamic weight adjustment mechanism played an important role, as different operating conditions affect the relative importance of each objective. Therefore, by adjusting the weights in real time, this ensures that each objective is reasonably optimized according to different situations. Candidate solutions with higher fitness values indicate better performance in multi-objective optimization problems.

After fitness assessment, individuals can undergo Pareto sorting. The core of Pareto sorting is to retain solutions that are not dominated by other individuals, known as Pareto frontier solutions. These solutions achieve good equilibrium across multiple objectives, reflecting the concept of global optimality. To ensure population diversity, Pareto frontier solutions can be retained in each generation, but the best performing individuals can also be directly introduced into the next generation population through elite strategies. This prevents population degradation and ensures that the optimal solution is retained in each generation of the population.

The population update strategy is a key step in the optimization process, generating new individuals through crossover and mutation operations, exploring new solution spaces, and improving the search ability for global optimal solutions. Cross-operation combines two parent individuals to generate offspring, and the mutation operation randomly modifies individual genes to enhance the global search ability of the algorithm. For the solution selection, elite strategies and diversity maintenance mechanisms based on Pareto sorting ensure that excellent and diverse individuals enter the next generation and not fall into local optima. The dynamic weight adjustment mechanism updates the objective function weights in real time according to changes in operating conditions, and combines elite strategy to retain the optimal solution, improving the global search ability and convergence efficiency of SPEA2 algorithm in nonlinear multi-objective optimization.

4. SIMULATION EXPERIMENT DESIGN

4.1 Experimental Scenarios and Testing Plans

For this study, several complex test scenarios were designed so as to cover typical road conditions such as sharp turns, uphill driving, slippery roads, and obstacle avoidance. The testing of sharp turning scenarios requires the vehicle to enter the curve at a certain speed, evaluate the yaw rate, body roll angle, and vehicle dynamic stability, and record the vehicle's motion posture and dynamic response through high-speed cameras and sensors. The hill driving experiment simulates the starting and climbing process of the vehicle under different slopes, focusing on the vehicle's power distribution strategy and power response time, and real-time monitoring of suspension system stiffness changes and body posture adjustments. The slippery road surface experiment is used to test the dynamic response of vehicles on low-friction coefficient roads, with a focus on determining the wheel slip rate and the timeliness of power distribution. The experimental platform simulates slippery road conditions by adjusting the road adhesion coefficient. The obstacle avoidance experiment simulates the obstacle avoidance ability of vehicles in sudden situations, examining the vehicle's lateral control and body posture adjustment. Several obstacles and various avoidance routes are used in the experiment to evaluate the system's response capability.

Standardized testing indicators have been introduced in various testing scenarios, including key performance parameters such as vehicle stability, power response time, body

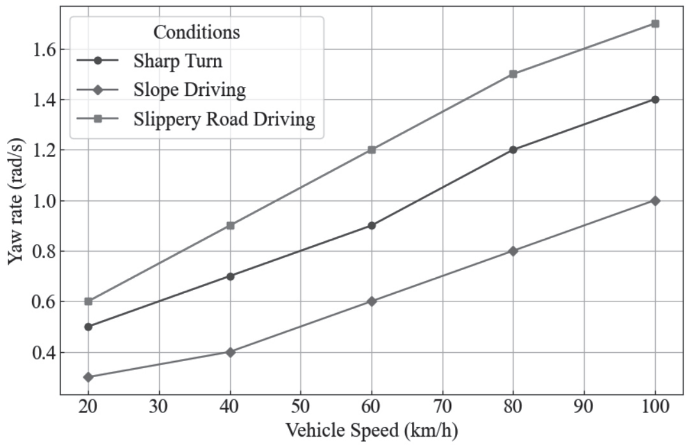

Figure 2 Changes in yaw rate under different operating conditions.

posture control, and yaw rate. In sharp turning scenarios, roll angle and yaw rate are core indicators. The goal of yaw rate is to maintain a certain safe range under high dynamic conditions. In the hill driving experiment, the power response time is the main evaluation metric. By shortening the response time, the stability and acceleration performance of the vehicle during starting on a slope can be improved. The slippery road experiment ensures the driving stability of the vehicle in low-friction coefficient environments by monitoring the wheel slip rate and power distribution ratio. Obstacle avoidance testing focuses on vehicle posture control and yaw rate, ensuring timely and stable adjustment of vehicle posture during rapid obstacle avoidance.

4.2 Performance Evaluation Indicators

To evaluate performance, the dynamic stability and safety of vehicles under complex working conditions were measured using four key indicators: yaw rate, body inclination angle, suspension stiffness, and power distribution ratio. The yaw rate reflects the stability of the vehicle during turning, and the calculation formula is the same as formula (7). The body inclination angle measures the attitude change of the vehicle during sharp turns or uphill driving, and the calculation formula is the same as formula (6). The suspension stiffness is used to describe the response capability of the suspension system under different speeds and terrains, and the calculation formula is the same as formula (4). The power distribution ratio ensures that the power output of the front and rear axles, as well as the left and right wheels, is balanced under different road conditions. The calculation formula is the same as formulas (8) and (9). By means of these indicators, the vehicle's handling performance and safety performance can be comprehensively evaluated.

5. RESULT ANALYSIS

5.1 Yaw Rate

This study evaluated the performance of vehicle control systems in dynamic environments through the monitoring and analysis of yaw rate. The results are shown in Figure 2.

In Figure 2, the yaw rate increases sharply from 0.5 rad/s at a speed of 20 km/h to 1.4 rad/s at 100 km/h in sharp turns, indicating posing a significant challenge to vehicle stability at high speeds. When driving on a slope, the increase in yaw rate is relatively small, reaching a maximum of 1.0 rad/s, indicating that the stability of the vehicle is relatively good. On slippery roads, the yaw rate increased from 0.6 rad/s at 20 km/h to 1.7 rad/s, indicating that slippery roads have a significant impact on vehicle yaw control. These data indicate that the yaw rate changes most significantly under slippery road surfaces and sharp turning conditions, and vehicle stability needs special attention in these situations.

5.2 Vehicle Tilt Angle

As the vehicle speed increases, the change in body inclination can significantly affect the handling and safety of the vehicle. During high-speed driving, the change in body inclination directly affects the stability and driving comfort of the vehicle. Figure 3 shows the relationship between vehicle speed and body inclination angle during sharp turns and uphill driving conditions.

Figure 3 shows that the influence of vehicle speed on the inclination angle of the vehicle is particularly significant during sharp turns. As the vehicle speed increases from 20 km/h to 100 km/h, the body inclination angle increases from 1.5° to 8.0°, reflecting an increasing trend of vehicle roll at high speeds. During hill driving, the change in vehicle inclination angle is relatively gentle, rising from 1.0° to 5.0°, indicating that hill driving has a relatively small impact on vehicle roll. Comprehensive analysis shows that the vehicle speed during sharp turns has the greatest impact on the body inclination angle. Therefore, it is necessary to strengthen the vehicle's roll control under this condition to improve driving stability.

5.3 Comparison of Power Response Time

To compare the impact of different optimization methods on power response time, two typical scenarios were used for testing and analysis purposes: uphill driving and obstacle avoidance. The selected optimization methods were:

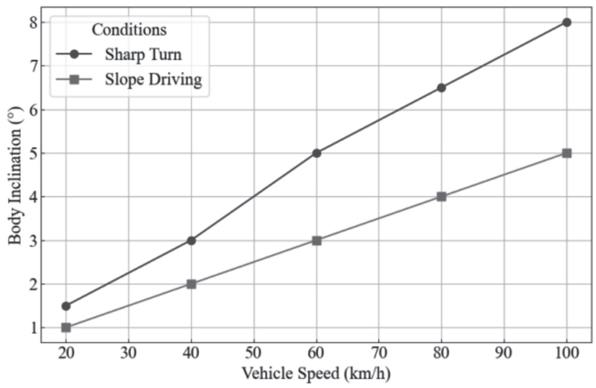

Figure 3 Relationship between vehicle speed and body inclination angle.

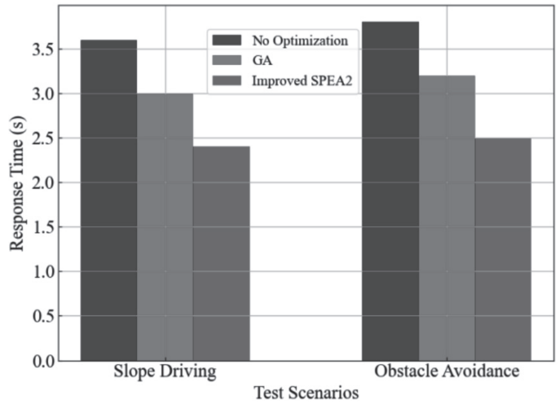

Figure 4 Comparison of power response time under different operating conditions.

unoptimized state, genetic algorithm, and improved SPEA2 algorithm. Power response time is an important indicator used to measure the performance of a vehicle in complex road conditions, indicating the rapidity of the power system's adaptability to changes in the external environment. By comparing the response times of different methods, the effectiveness of each optimization method in improving vehicle power response efficiency can be evaluated. Figure 4 shows the difference in dynamic response time of each method in these two scenarios.

The data in Figure 4 shows that the response time in the unoptimized state is 3.6 seconds and 3.8 seconds, respectively, in the scenarios of uphill driving and obstacle avoidance. After adopting the genetic algorithm, the response time was shortened to 3.0 seconds and 3.2 seconds. The improved SPEA2 algorithm performs the best, with response times of 2.4 seconds and 2.5 seconds respectively, showing a significant reduction. Compared to the unoptimized algorithm, it shortens the response time by 33.3% during hill driving. This comparison shows that the improved SPEA2 algorithm has significant advantages as it shortens the power response time and significantly improves the dynamic response performance of vehicles under difficult operating conditions.

5.4 Suspension System Stiffness Variation

The stiffness variation of the suspension system in difficult terrain is crucial for the vehicle's handling performance and safety, especially in different working conditions such as sharp turns, uphill driving, and slippery roads. The system needs to dynamically adjust the suspension stiffness according to road conditions and vehicle speed. In this study, a multi-objective optimization model is constructed to test the stiffness changes of the suspension system at different speeds, in order to evaluate its adaptability in various environments. Figure 5 shows the suspension stiffness adjustment of the vehicle as a function of vehicle speed under three typical operating conditions.

Figure 5 shows that as the vehicle's speed increases, the overall suspension stiffness increases. Under sharp turning conditions, the suspension stiffness increased from 12000 N/m at 20 km/h to 15000 N/m at 100 km/h, indicating that the system increased stiffness to cope with higher lateral forces. During uphill driving, the stiffness changes relatively gently, increasing from 10000 N/m to 12000 N/m, indicating that the system pays more attention to stability in this scenario. The change in stiffness under slippery road conditions is relatively small, with a maximum value of 10500 N/m, reflecting the system's need to consider a greater reduction of wheel slip. These data have verified the optimization effect of the suspension system under different working conditions, demonstrating its adaptability and flexibility in dealing with different road conditions.

5.5 Comparison of Wheel Slip Rates

When driving on slippery roads, the stability of the vehicle depends mainly on the slip rate of the wheels, and different

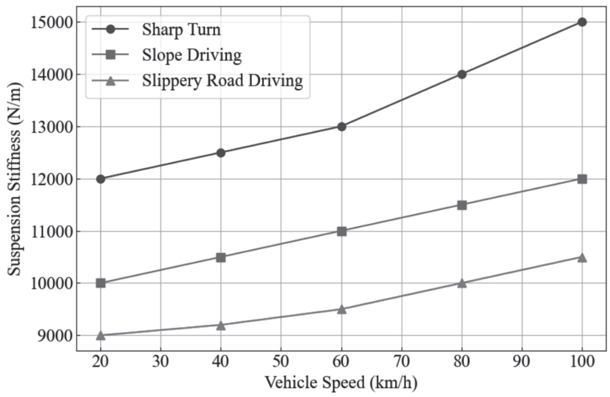

Figure 5 Suspension stiffness variation under different operating conditions.

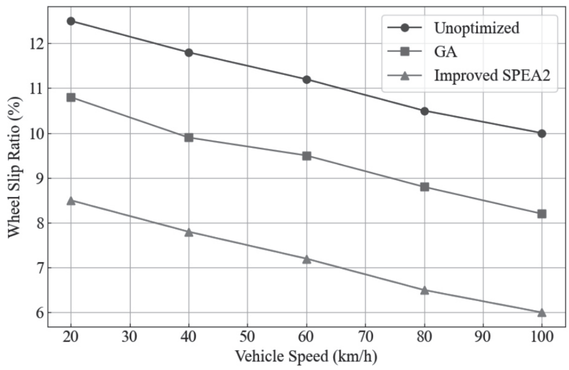

Figure 6 Comparison of wheel slip rates on slippery road surfaces.

control algorithms have significant differences in terms of reducing slip rate. The control effect of slip rate directly affects the vehicle's grip performance and power output, so it is crucial to evaluate the effectiveness of control methods in complex road conditions. In this study, slip rate tests were conducted on wet road surfaces using unoptimized state, genetic algorithm, and improved SPEA2 algorithm. Figure 6 shows the variation of slip rate with vehicle speed under each control method.

Figure 6 shows that the slip rate in the unoptimized state is 12.5% at a speed of 20 km/h, and decreases to 10.0% as the speed increases to 100 km/h. Genetic algorithm performs better at the same speed, reducing the slip rate from 10.8% to 8.2%, demonstrating improvement on slippery road surfaces. The improved SPEA2 algorithm performs the best, with the slip rate gradually decreasing from 8.5% to 6.0%. This result indicates that the improved SPEA2 algorithm offers significant advantages in reducing the slip rate on slippery roads, and significantly improving vehicle stability.

5.6 Power Distribution Ratio

The distribution of power in vehicles traversing difficult terrains is crucial for maintaining driving stability. Appropriate power distribution can effectively improve the handling and safety of vehicles in different working conditions such as sharp turns, uphill driving, and slippery roads. Through power distribution optimization algorithms, especially the improved SPEA2 algorithm, the power distribution ratio between the front and rear axles and the left and right wheels of the vehicle has been adjusted to ensure that each wheel is evenly stressed and provides sufficient traction under different working conditions. Figure 7 shows the power distribution ratio between the front and rear axles and the left and right wheels of the vehicle under different operating conditions.

The data in Figure 7 shows that under sharp turning conditions, the power distribution ratio between the front and rear axles is 60% for the front axle and 40% for the rear axle, while the distribution between the left and right wheels is 55% for the left wheel and 45% for the right wheel. When driving on a slope, the power distribution between the front and rear axles reaches a balance of 50% each, while the distribution ratio between the left and right wheels is 52% for the left wheel and 48% for the right wheel. Under slippery road conditions, there is more power in the rear axle, with a ratio of 40% in the front axle and 60% in the rear axle. The distribution of left and right wheels remains balanced, with each wheel being 50%. These data indicate that the SPEA2 algorithm effectively optimizes the power allocation ratio, ensures the balance of power output of vehicles under different road conditions, and improves driving stability under difficult road conditions.

6. CONCLUSIONS

The multi-objective optimization method based on the improved SPEA2 algorithm proposed in this article successfully solves the multi-objective balance problem of vehicle suspension system and power allocation strategy in complex,

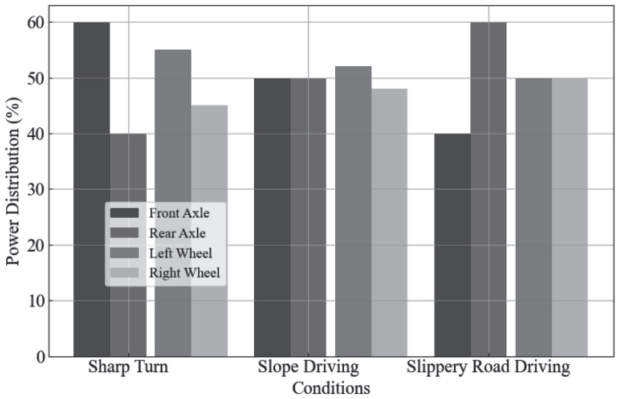

Figure 7 Comparison of power distribution ratios under different operating conditions.

dynamic environments. This method optimizes the suspension stiffness, body posture, and power allocation ratio by introducing elite strategy and Pareto ranking, significantly improving the dynamic performance of the vehicle. The experimental results show that the system performs well in typical working conditions such as sharp turns, uphill driving, and slippery roads, and the vehicle's anti-rollover ability and dynamic response time are significantly improved. Despite achieving good results, there is still room for improvement in the convergence speed and real-time performance of the algorithm in more extreme environments. Future research will focus on investigating real-time optimization methods and more intelligent suspension systems to further enhance the stability and safety of vehicles.

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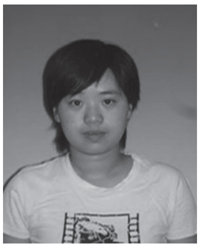

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