

# Optimization Design for Suspension System Based on Response Surface Method and NCGA Algorithm

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**Abstract.** For effective and quick selection of hard point coordinate parameters of suspension to improve the handling stability of vehicles, an optimization method was put forward to some certain suspension system by combining the response surface method and NCGA algorithm. A dynamics simulation model was established first to the Macpherson suspension system of some certain mini-van and the sensitivity analysis was carried out to hard point coordinates of the corresponding suspension to find the coordinate parameters whose sensitivities are higher; moreover, an approximate mathematical model was established between the wheel alignment parameters and the selected coordinate parameters in accordance with the response surface method and the corresponding accuracy verification was carried out; and the positioning parameters were grouped rationally and the unified objective function was established by utilizing the direct weighting method; in addition, optimization design was carried out to the established objective function by combining the neighborhood cultivation genetic algorithm (NCGA). Results indicate that the optimized positioning parameter variables are reduced in different degrees so as to further improve the handling stability of vehicles and verify some certain effectiveness of our methods.

**Keywords:** Suspension, Positioning parameters, Response surface method, NCGA, Multi-objective optimization.

## 1. Introduction

The changing positioning parameters of bumping vehicle wheels are important factors for influencing vehicle handling stability and service life of tires [1]. To lower bumping wheel positioning variables by changing hard points of the suspension structure is an effective method for improving suspension performances so as to perform extensive studies. FENG Jinzhi et al. [2] optimized hard points of the suspension structure by utilizing NSGA, whose computational burden is great without simplification of the suspension based on the multi-body dynamics model; DING Fei et al. [3] established the dynamic mathematical model to the link system of suspension by utilizing the limited rotation tensor and vector algebra method and optimization was carried out by utilizing the micro multi-objective genetic algorithm to obtain the hard point coordinates of the suspension satisfying different preferences without optimization of differences between relative importance and orders of magnitude of objective camber angles, toe angles and lateral slips at wheel centers. In view of the above problem, an optimization design method was put forward to the suspension system in this study by combining the response surface method and NCGA, whose optimization objective is the minimum bumping variables of front wheel positioning parameters. A dynamic simulation model was established to the Macpherson suspension system of some certain mini-van and parallel travel simulation test was carried out to dual wheels of the suspension.

In view of there being many design variables, sensitivity analysis was carried out to hard point coordinates of the suspension to choose several pairs of parameters with higher sensitivities for testing again; moreover, an approximate mathematical model was established by utilizing the test data for the second time in accordance with the response surface method in view of great calculation of the suspension simulation model to reduce the computing time; furthermore, four alignment parameters were grouped by utilizing the weighting combination method based on taking their roles and

importance; in addition, NCGA was utilized to improve the searching performance of the multi-objective optimization algorithm.

## 2. Model Calculation

### 2.1 Front Suspension Model

The following simplifications and assumptions are taken to establish the dynamic model: all parts except elastic components and rubber elements are regarded as rigid bodies; and all connections between parts are simplified as rigid hinges. The front suspension of some certain mini-van is the Macpherson type and is primarily made up of a control arm, a knuckle assembly, absorbers and a tie rod. The key hard point coordinates of the CAD model, other mass characteristic parameters and mechanical characteristics parameters of springs, bushings and absorbers are from designers of the manufacturer. A dynamic simulation model was established to the Macpherson suspension by utilizing the multi-body dynamics software (ADAMS/Car) [4], as shown in Fig. 1.

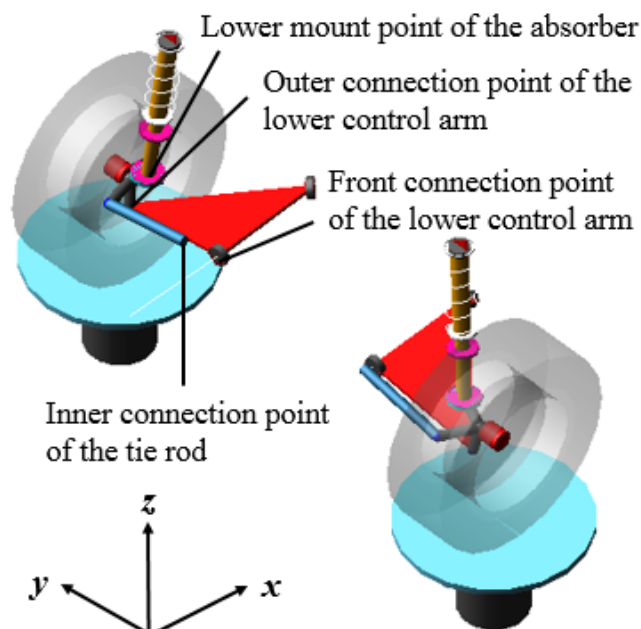


Figure 1. Dynamic model of Macpherson suspension

### 2.2 Sensitivity Analysis of Hard Point Coordinates of the Suspension

Sensitivity analysis was carried out in ADAMS/Insight. Due to there being many hard point parameters of the front suspension and great computational burden, those insensitive hard point parameters are ignored in accordance with engineering experiences, x, y and z coordinates of 5 hard points (such as the lower mount point of the absorber, the inner connection point of the tie rod, the front connection point of the lower control arm, the rear connection point of the lower control arm and the outer connection point of the lower control arm) are selected as design variables.

Table 1. Sensitivity positioning parameters

| NO.   | Camber angle/% | Toe angle/% | Kingpin caster angle/% | Kingpin inclination angle/% |
|-------|----------------|-------------|------------------------|-----------------------------|
| $x_1$ | -5.34          | 76.98       | 0.25                   | 0.24                        |
| $x_2$ | -2.7           | 10.72       | 6.18                   | -1.5                        |
| $x_3$ | 12.75          | -48.6       | -29.87                 | 7.1                         |
| $x_4$ | 2.37           | -8.93       | -0.5                   | -2.69                       |
| $x_5$ | -11.25         | 42.77       | 2.99                   | -5.42                       |
| $x_6$ | -6.04          | -6.82       | 0.16                   | 0.15                        |

If all 15 coordinates of the above hard points were optimization variables, the necessary iteration number would be very big; thus, sensitivity analysis shall be carried out to those positioning ones of 15 coordinates to obtain 6 points with maximum sensitivities [5]: y-coordinate  $x_1$  of the lower mount point of the absorber, z-coordinate  $x_2$  of the inner connection point of the tie rod, y-coordinate  $x_3$  of the front connection point of the lower control arm, z-coordinate  $x_4$  of the front connection point of the lower control arm, y-coordinate  $x_5$  of the outer connection point of the lower control arm, and z-coordinate  $x_6$  of the outer connection point of the lower control arm; and they are regarded as optimization variables, whose sensitivity analysis results are shown in Table 1.

### 3. Approximate mathematical model

#### 3.1 Design of Experiment

A certain number of experiment design data are necessarily taken into account to establish an approximation model for the response surface and the experiment design samples can reflect the entire design space. The central composite experiment design is popular for establishment of second-order response surface models, whose advantages lie in supply of abundant information about test variables and errors and capacity of fitting second-order relationships. Table 2 shows our central composite experiment design scheme.

**Table 2.** Central composite experiment design

| Scheme | x1/mm   | x2/mm | x3/mm   | x4/mm   | x5/mm   | x6/mm   |
|--------|---------|-------|---------|---------|---------|---------|
| 1      | -589.11 | -62.9 | -293.18 | -147.18 | -639.24 | -219.86 |
| 2      | -589.11 | -62.9 | -293.18 | -147.18 | -629.24 | -209.86 |
| 3      | -589.11 | -62.9 | -293.18 | -137.18 | -639.24 | -209.86 |
| 4      | -589.11 | -62.9 | -293.18 | -137.18 | -629.24 | -219.86 |
| 5      | -589.11 | -62.9 | -283.18 | -147.18 | -639.24 | -209.86 |
| ...    | ...     | ...   | ...     | ...     | ...     | ...     |
| 45     | -579.11 | -52.9 | -293.18 | -147.18 | -629.24 | -209.86 |

#### 3.2 Approximation Model of the Response Surface

The response surface method is to approximately construct a polynomial function in the clear expression mode to perform modeling analysis to the relationship between response objectives and various variables. The second-order response surface model is more accurate for description of the relationship between design response and variables than any other method (such as the neural network method) due to its linear, quadratic and cross terms [6]. The second order response surface approximation model is expressed as follows:□

$$y = \beta_0 + \sum_{i=1}^n \beta_i x_i + \sum_{i=1}^n \beta_{ii} x_i^2 + \sum_{1 \leq i < j}^n \beta_{ij} x_i x_j + \varepsilon \quad (1)$$

where,  $\beta_0$ ,  $\beta_i$ ,  $\beta_{ii}$  and  $\beta_{ij}$  represent the regression coefficients, whose number is  $N = (n+2)(n+1)/2$ ; and  $\varepsilon$  represents the approximation error, which may be regarded as  $\varepsilon=0$  in case of meeting the engineering accuracy requirement.

Based on the above experiment design, the obtained data are fitted by utilizing the least square method to get 28 groups of regression coefficients of the second-order response surface model, as shown in Table 3.

**Table 3.** Regression coefficients of the response surface model

| <b>Regression coefficient</b> | <b>Toe angle</b> | <b>Camber angle</b> | <b>Kingpin caster angle</b> | <b>Kingpin inclination angle</b> |
|-------------------------------|------------------|---------------------|-----------------------------|----------------------------------|
| $\beta_0$                     | 59.35263         | -3.04926            | -0.08696                    | -2.41046                         |
| $\beta_1$                     | -0.20243         | -0.00437            | 0.000771                    | -0.00317                         |
| $\beta_2$                     | -0.05828         | 0.020205            | -0.00318                    | 0.013991                         |
| $\beta_3$                     | -0.42531         | 0.004474            | 0.002538                    | -0.00554                         |
| $\beta_4$                     | -0.1367          | -0.02457            | -0.00564                    | -0.01769                         |
| $\beta_5$                     | -0.11847         | -0.00491            | 2E-05                       | 0.00077                          |
| $\beta_6$                     | 0.837554         | -0.00636            | -0.00057                    | 0.00265                          |
| <b>Regression coefficient</b> | <b>Toe angle</b> | <b>Camber angle</b> | <b>Kingpin caster angle</b> | <b>Kingpin inclination angle</b> |
| $\beta_{12}$                  | -0.00016         | -2.60E-05           | 2.00E-05                    | -1.70E-05                        |
| $\beta_{13}$                  | -0.0003          | -9.40E-06           | 4.09E-06                    | -7.40E-06                        |
| $\beta_{14}$                  | 0.000232         | 2.21E-05            | -1.90E-05                   | 1.61E-05                         |
| $\beta_{15}$                  | 0.000386         | -1.30E-06           | 5.75E-07                    | -6.60E-07                        |
| $\beta_{16}$                  | -0.00028         | -1.40E-06           | 2.66E-07                    | -3.70E-07                        |
| $\beta_{23}$                  | 0.000179         | 1.79E-05            | 2.48E-06                    | 1.58E-05                         |
| $\beta_{24}$                  | -0.00061         | 2.69E-05            | -1.60E-05                   | 1.44E-05                         |
| <b>Regression coefficient</b> | <b>Toe angle</b> | <b>Camber angle</b> | <b>Kingpin caster angle</b> | <b>Kingpin inclination angle</b> |
| $\beta_{25}$                  | -0.00078         | 6.80E-06            | -1.90E-06                   | 1.15E-06                         |
| $\beta_{26}$                  | 0.000173         | 3.20E-06            | -9.60E-07                   | 4.82E-07                         |
| $\beta_{34}$                  | -0.00031         | -1.50E-05           | 9.11E-07                    | -2.60E-05                        |
| $\beta_{35}$                  | -0.00032         | 3.59E-06            | 1.66E-07                    | 5.90E-07                         |
| $\beta_{36}$                  | 0.000236         | 2.87E-06            | 5.81E-07                    | 2.20E-06                         |
| $\beta_{45}$                  | 0.001275         | -1.30E-05           | 2.19E-07                    | -3.40E-07                        |
| $\beta_{46}$                  | -0.00038         | -1.30E-05           | 2.67E-07                    | -2.60E-07                        |
| <b>Regression coefficient</b> | <b>Toe angle</b> | <b>Camber angle</b> | <b>Kingpin caster angle</b> | <b>Kingpin inclination angle</b> |
| $\beta_{56}$                  | -0.00046         | -8.60E-07           | -1.60E-07                   | 4.54E-07                         |
| $\beta_{11}$                  | 0.000162         | 5.80E-06            | -4.00E-06                   | 3.66E-06                         |
| $\beta_{22}$                  | -6.10E-05        | -4.20E-06           | 4.43E-06                    | -4.00E-06                        |
| $\beta_{33}$                  | -0.00032         | 3.37E-06            | 4.66E-07                    | 7.75E-07                         |
| $\beta_{44}$                  | 0.00046          | -1.90E-05           | 1.48E-06                    | -7.00E-06                        |
| $\beta_{55}$                  | 0.000211         | -4.10E-06           | 6.54E-08                    | 6.29E-08                         |
| $\beta_{66}$                  | 0.00073          | -7.50E-07           | -8.30E-07                   | 1.02E-06                         |

### 3.3 Verification of the Response Surface Approximation Model

While performing optimization design by using the response surface method, inspection shall necessarily be carried out to the fitted response surface model and the multiple correlation coefficient ( $R^2$ ) is generally used to evaluate its fitting degree [7]:

$$R^2 = 1 - \frac{SSE}{SSY} \quad (2)$$

$$SSE = \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (3)$$

$$SSY = \sum_{i=1}^n y_i^2 - \frac{1}{n} \sum_{i=1}^n \hat{y}_i \quad (4)$$

where, SSE represents the sum of squares of deviations of response and estimate values, SSY represents the sum of squares of response and mean values, n represents the number of evaluation points,  $y_i$  represents the simulation output values,  $\hat{y}_i$  represents the response surface function values, and  $R^2$  changes in the interval  $([0,1])$  and becomes more accurate while it is closer to 1. The reliability verification results of various parameters are shown in Table 4.

**Table 4.** Reliability verification results

|       | Toe angle | Camber angle | Kingpin caster angle | Kingpin inclination angle |
|-------|-----------|--------------|----------------------|---------------------------|
| $R^2$ | 0.9348    | 0.9672       | 0.9492               | 0.9932                    |

Various reliability correlation coefficients in the above table are within their allowable accuracies and very close to 1 to indicate that our response surface model is relatively accurate; thus, it is judged that optimization may be carried out by using the response surface approximation model fitted by using the simulation data in place of the actual one.

## 4. Optimization design

### 4.1 Objective Function

Our optimization is to improve the vehicle handling stability and relieve wearing of tires by reducing wheel bumping positioning variables. The toe angle is set to fit the front wheel camber angle to relieve wearing of tires; and the kingpin inclination angle and caster are to generate the aligning torque and lower the steering force. In accordance with the above analysis, the front wheel positioning parameters are divided into two groups (one group: the front wheel toe angle and camber angle; and the other group: the kingpin inclination angle and caster). Each group of parameters is set as an objective function by utilizing the weighting combination method, whose form is as follows:

$$f_1(x) = \omega_1 y_1(x) + \omega_2 y_2(x) \quad (5)$$

$$f_2(x) = \omega_3 y_3(x) + \omega_4 y_4(x) \quad (6)$$

Where,  $\omega_i$  represents the weight coefficient of the component objective function  $y_i(x)$ , whose value depends on orders of magnitude and importance of its various objectives. For easy calculation of vehicle handling stability and wearing of tires influenced by various component objectives, the unified objective function was established in this study by utilizing the direct weighting method, whose weight coefficient  $\omega_i$  was selected in accordance with the following method [8].

If the changing range of some certain component objective function  $y_i(x)$  is known:

$$\alpha_i \leq y_i(x) \leq \beta_i \quad (i = 1, 2, 3, 4) \quad (7)$$

Then:

$$\Delta y_i(x) = \frac{\beta_i - \alpha_i}{2} \quad (8)$$

It is the tolerance of this objective, and then its weight coefficient may be taken as:

$$\omega_i(x) = \frac{1}{(\Delta y_i(x))^2} \quad (9)$$

This selection method is based on the requirement for tending to achieve the unified balance in orders of magnitude of various component objective functions of the unified objective function. The more broadly an objective function changes, the larger its objective tolerance is but the smaller its weight coefficient is; on the other hand, the more narrowly it changes, the smaller its objective tolerance is but the larger its weight coefficient is; thus, the orders of magnitude of various component objective functions may be balanced.

The ranges of various objective variables are determined in accordance with simulation test analysis and then their tolerances and weight coefficients in accordance with calculation equations to obtain weight coefficients of various positioning parameters of wheels, as shown in Table 5.

**Table 5.** Weight coefficients of various objective variables

| Objective variable | Range of variable/ <sup>o</sup> | Weight coefficient |
|--------------------|---------------------------------|--------------------|
| $y_1(x)$           | $-0.38 \leq y_1(x) \leq 1.94$   | 0.74               |
| $y_2(x)$           | $-0.64 \leq y_2(x) \leq 2.00$   | 0.57               |
| $y_3(x)$           | $3.89 \leq y_3(x) \leq 4.43$    | 4.43               |
| $y_4(x)$           | $7.05 \leq y_4(x) \leq 10.18$   | 0.41               |

The following objective function may be obtained in accordance with weight coefficients of various component objective functions stated above:

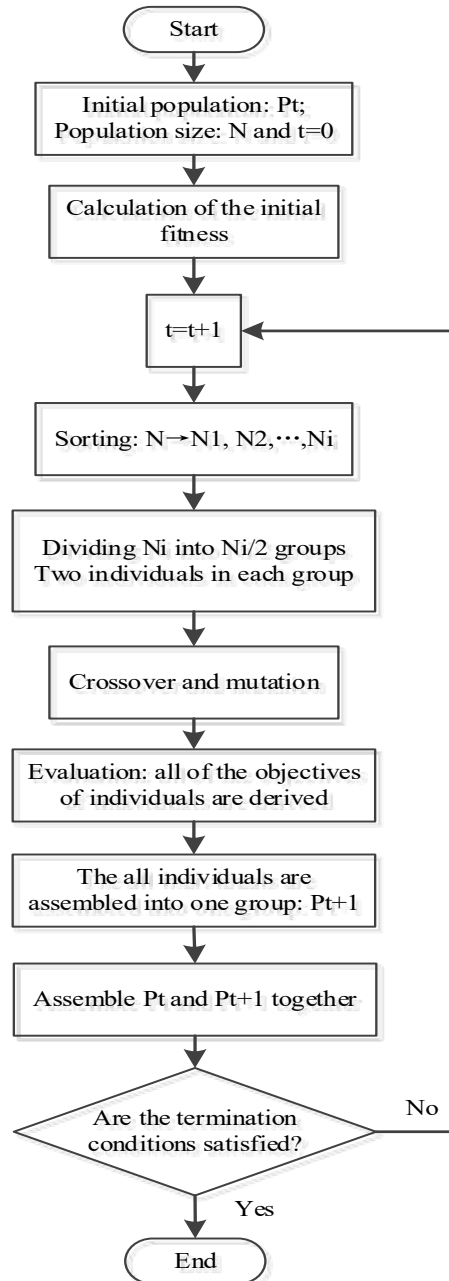
$$\begin{cases} f_1(x) = 0.74y_1(x) + 0.57y_2(x) \\ f_2(x) = 4.43y_3(x) + 0.41y_4(x) \end{cases} \quad (10)$$

After completion of the weighted combination, optimization of positioning parameters of wheels is converted into optimization of 2 objectives (positioning of steering knuckle and kingpin), and the system optimization model is expressed as:

$$\begin{cases} \min f_1(x) \\ \min f_2(x) \\ \text{s.t. } x_i^L \leq x_i \leq x_i^H, i = 1, 2, 3, 4, 5, 6 \end{cases} \quad (11)$$

## 4.2 Multi-objective optimization NCGA

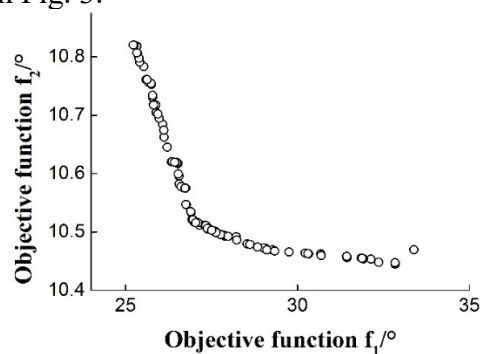
Currently, the multi-objective optimization algorithms primarily includes the vector evaluated genetic algorithm (VEGA), the multi-objective genetic algorithm (MOGA), the niched Pareto genetic algorithm (NPGA) and the non-dominated sorting genetic algorithm II (NSGA-II) [9-12] which integrates those strategies (such as elitist, density valuation and fast non-dominated sorting) and NSGA to improve the calculation speed; on the other hand, its disadvantage lies in its Pareto ranking method limits its searching performance to some extent. In contrast, the neighboring crossover strategy is utilized in our NCGA [13] to greatly improve its searching performance, whose flow diagram is shown in Fig. 2 and where the used parameters are: population size: 100; crossover probability: 0.8; mutation probability: 0.05; and evolution generations: 50.



**Figure 2.** NCGA flow diagram

#### 4.3 Optimization results and analysis

After repeated iteration optimization, the Pareto optimal solution set of the multi-objective optimization problem is shown in Fig. 3.



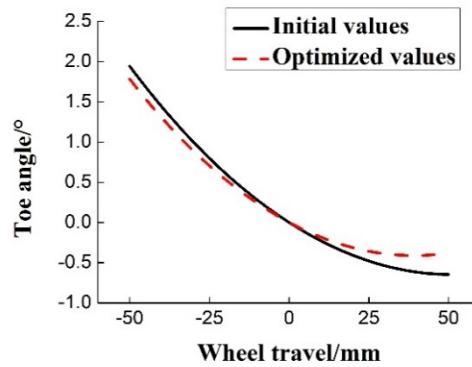
**Figure 3.** Pareto solution set of the multi-objective optimization problem

It may be seen from Fig. 3 that 2 objective functions conflict with each other and changing one objective function may lead to changing the other one; thus, designers may select a certain group of optimal solution in accordance with the specific requirements of the suspension among several solutions of the multi-objective optimization problem to satisfy the design requirements; and then those suspension parameters such as camber angle, toe angle, kingpin caster and kingpin inclination angle may be determine appropriately. A group of optimal solution values here in accordance with the specific requirements is shown in Table 6.

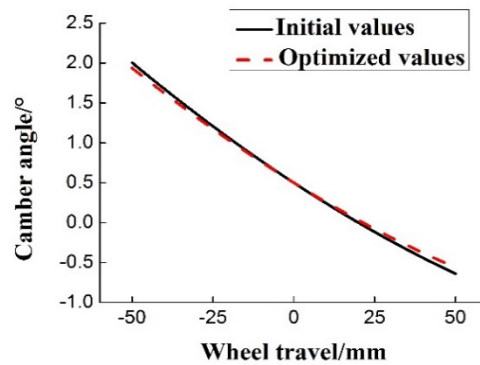
**Table 6.** Pareto solution set of our multi-objective optimization problem

|                  | $x_1/\text{mm}$ | $x_2/\text{mm}$ | $x_3/\text{mm}$ | $x_4/\text{mm}$ | $x_5/\text{mm}$ | $x_6/\text{mm}$ |
|------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Coordinate value | -589.06         | -61.76          | -293.18         | -137.22         | -629.27         | -209.86         |

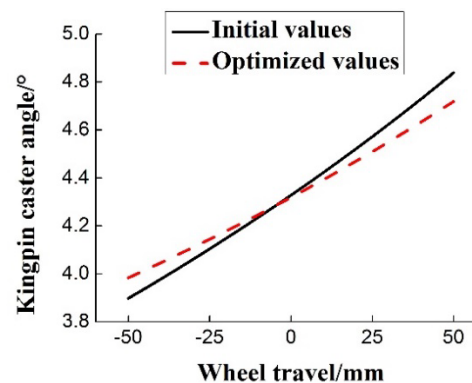
For verification of NCGA optimization effects, the comparison analysis was carried out to the initial and optimized toe angles, camber angles, and kingpin casters and inclination angles, whose results are shown in Fig. 4 and Table 7.



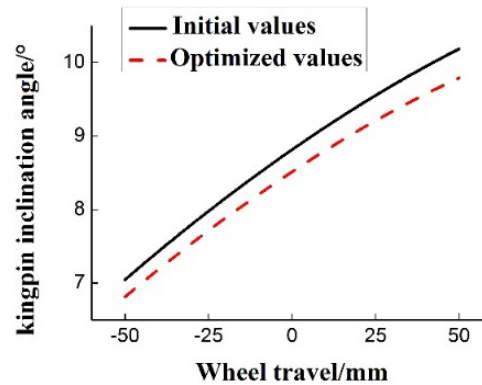
(a) Variation of toe angle before and after optimization



(b) Variation of camber angle before and after optimization



(c) Variation of kingpin caster before and after optimization



(d) Variation of kingpin inclination angle before and after optimization

**Figure 4.** Variation of positioning parameters before and after optimization

**Table 7.** Comparison of positioning parameters before and after optimization

| Alignment parameter       | Initial variable /° | Optimized variable /° | Optimization percentage /% |
|---------------------------|---------------------|-----------------------|----------------------------|
| Toe angle                 | 2.795               | 2.194                 | 21.50                      |
| Camber angle              | 2.687               | 2.518                 | 6.29                       |
| Kingpin caster angle      | 0.969               | 0.735                 | 24.15                      |
| Kingpin inclination angle | 3.134               | 3.076                 | 1.85                       |

The wheel toe angle is to reduce the influence of the front wheel camber angle to the suspension system, wearing of tires and the rolling friction resistance of wheels, prevent any outward motion of wheels and improve the vehicle handling stability. It may be seen from Fig. 4(a) and Table 7 that the variation of the initial toe angle is  $2.795^\circ$  which is relatively large but the optimized toe angle is  $2.194^\circ$ . The variation of the optimized toe angle is obviously reduced but the vehicle steering performance is improved to some extent.

Due to the vehicle handling stability, smoothness and steering behavior being directly affected by the wheel camber angle, the variation of the camber angle for bumping wheels shall be reduced as can as possible to ensure the vehicle safety. It is known from Fig. 4(b) and Table 7 that the variation of the initial camber angle is  $2.687^\circ$  but the variation of the optimized camber angle is  $2.518^\circ$ , which is reduced slightly to be beneficial to improving the vehicle handling performance.

Design of the kingpin caster angle is to produce the aligning torque and enhance the stability of straight driving. As for bumping wheels, it is required that the kingpin caster angle shall be small as can as possible to prevent too high or low aligning torque due to any load change and influence the vehicle handling stability. It is known by combining Fig. 4(c) and Table 7 that the variation of the optimized kingpin caster angle is  $0.735^\circ$  which is lowered by 24.15% in comparison with the variation of the initial kingpin caster angle ( $0.969^\circ$ ); thus, the effect is remarkable and the vehicle stability is improved.

The kingpin inclination angle is helpful to reduce the kingpin lateral offset so as to reduce the drivers' steering force and easily handle the steering wheels; moreover, the impact of wheel from steering wheels may be reduced. Fig. 4(d) and Table 7 indicate that the variations of the initial and optimized kingpin inclination angles are  $3.134^\circ$  and  $3.076^\circ$ , respectively, and the optimization percentage is 1.85%; thus, the vehicle steering portability is improved to some extent.

## 5. Conclusions

a. An approximate mathematical model was established between wheel alignment parameters and selected coordinate parameters by utilizing the response surface method, whose verified accuracy is relatively high; thus, it may be used to replace accurately the actual model for performance of analysis and calculation.

b. Our NCGA may be used to quickly search the Pareto optimal solution set of the multi-objective problem and present the rational optimization solution in accordance with requirements for optimization of the suspension parameters.

c. The optimization results indicate that our method is effective for optimization of Macpherson suspensions and may act as effective optimization guidance to designers. Although our object of research is a Macpherson suspension, our optimization method is also of guiding significance to be of guiding significance to optimization other types of suspensions.

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