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Robust Optimization of High-Speed Rail Vehicle Suspension Parameters Based on Vertical Running Stability

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Keywords ：rail vehicle, vertical running stability, suspension parameters, Taguchi method, robust optimization.

ABSTRACT

Since noise factors have a significant influence on vertical running stability of high-speed rail vehicles, robust optimization of the suspension parameters can improve the robustness of vehicle under different running conditions, and thus ensure running quality. Vertical stiffness and damping of primary and secondary suspensions were here regarded as controllable factors, with speed, passenger capacity and railway curve radius selected as noise factors. Then Taguchi method was introduced to construct a basic robust optimization model of vehicle suspension parameters. Based on the advantages of non-linear fitting of Radial Basis Function (RBF) surrogate model, an RBF surrogate model of vehicle vertical running stability was constructed to analyze the influence of both controllable factors and noise factors. On this basis, the suspension parameter combination with best robustness was determined through internal and external orthogonal testing of the controllable factors and noise factors, as well as signal-to-noise ratio analysis. The results indicated that, after robust optimization of the suspension parameters, the mean value of the vertical running stability index under different running conditions was improved by 7.55%, and the amplitude of vertical running stability index over the whole range was reduced by 31.0%, which validated the effectiveness of the proposed method.

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INTRODUCTION

Vertical running stability is an important index employed to quantify the running quality of high-speed rail vehicles, which is significantly influenced by the mutual matching of suspension parameters (Cao et al., 2016). The suspension system of high-speed rail vehicles is a multi-parameter complex system composed of primary and secondary suspensions, whose parameters can be optimized in order to improve running stability and ensure vehicle running quality (Gialleonardo et al., 2012). Many scholars have carried out research on the design optimization of vehicle suspension parameters in recent years. Liao (2012) used a multi-objective optimization method based on a genetic algorithm to optimize the suspension parameters of high-speed rail vehicles, improving curving behaviors but also reducing the running stability of vehicles. Having confirmed certain derailment coefficients as the major parameters on the basis of the partial least squares method, Ying et al. (2015) established a Kriging surrogate model and optimized the thresholds of suspension parameters, thereby acquiring the latter's maximum feasible interval. Sayyaadi and Shokouhi (2009) introduced a complete nonlinear thermo-dynamic air spring model and optimized the air suspension parameters of rail vehicles using the Genetic Algorithm optimization method, improving riding comfort and reducing values of the ride comfort index by about 10%. Baek et al. (2013) optimized the suspension parameters of high-speed electric multiple units with ten degrees of freedom, reducing the vertical vibration of the vehicles. Chen et al. (2015) built a multi-body dynamic rigid-flexible coupling model based on the multi-body system dynamics, then he created a kriging model to describe the relationship of vehicle ride comfort evaluation indices and suspension parameters. The vehicle ride

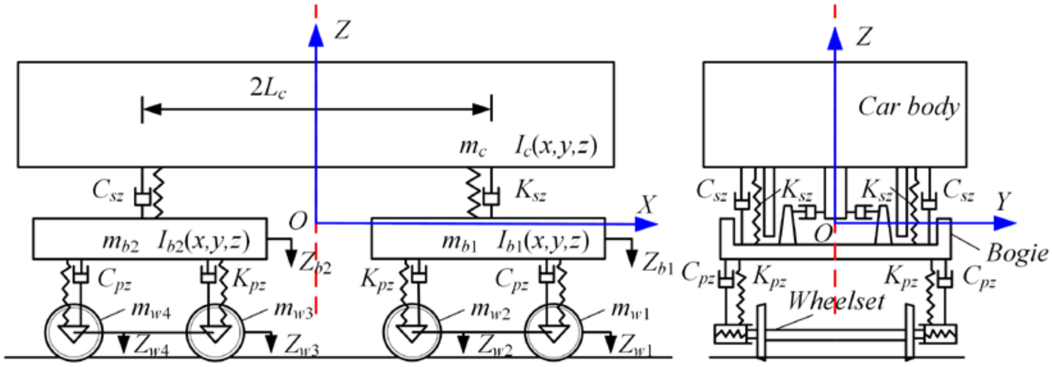

Fig. 1 Vertical dynamics model of a rail vehicle

comfort performance was improved after multi-objective optimization using NSGA-II.

However, these previous studies were carried out under stable running conditions and did not consider noise factors during the vehicle running process, such as the railway curve radius, speed, and passenger capacity. All of these factors have an influence on vehicle vertical running stability and can lead to the absence of optimal running stability when the above suspension parameters are adopted under multiple running conditions (Shen, 2013).

In the present paper, noise factors were taken into consideration due to their significant influence on the vertical running stability of vehicles, with the robust optimization method introduced in the development of research aimed at the robust optimization of the suspension parameters of high-speed rail vehicles. The RBF surrogate model was then used to simulate the complex non-linear relationship between suspension parameters and vertical running stability. Suspension parameter combination with optimum robustness under the influence of noise factors was obtained via internal and external orthogonal testing of controllable factors and noise factors, with signal-to-noise ratio analysis carried out to achieve robust optimization of the suspension parameters under multiple running conditions.

ROBUST OPTIMIZATION STRATEGY

Controllable factors and noise factors

The robust design method is widely employed to ensure the stable performance of products even when the environment or product parameters are changed. In the robust design process, those factors that can be determined by designers are known as controllable factors, with those that can't known as noise factors; uncertainty in the latter can thus have a significant influence on system output. In order to identify the controllable factors and noise factors that affect the vertical running stability of vehicles, a vertical dynamic model is often developed.

High-speed rail vehicles can be regarded as multi-body systems consisting of a car body, two frames, four wheel-sets, primary suspension, and secondary suspension. The wheel-sets and the frame are connected by the primary suspension, and the frame and the car body by the secondary suspension, together forming a complete suspension system. A vertical dynamics model of a typical rail vehicle (Yang et al., 2014) is shown in Figure 1.

The parameters K_{pz}, C_{pz}, K_{sz} and C_{sz}, whose values can be selected within a certain range, affect vehicle vertical running stability significantly (Yang et al., 2015, Chi et al., 2007). These four parameters were thus selected here as the controllable factors, represented as $C\{K_{pz}$ 、C_{pz} 、K_{sz} 、$C_{sz}\}$.

The passenger capacity of a vehicle changes during the running process, leading to the variation of vehicle gravity and affecting the vertical running stability. The braking and acceleration of a vehicle during the running process affect vehicle speed and dynamic performance, while the railway curve radius is different on different lines, also resulting in changes to the vertical running stability of the vehicle (Liao et al., 2011). Therefore, speed, passenger capacity and railway curve radius were selected as the noise factors, represented as $N\{v$ 、M 、$R\}$.

Basic robust optimization model

For the robust optimization of vehicle suspension parameters, the vertical running stability index W was taken as the optimization target, the suspension parameters $C\{K_{pz}$ 、C_{pz} 、K_{sz} 、$C_{sz}\}$as the optimization parameters, and the surrogate model of vertical running stability as the optimization target function. Considering the standard constraint value and the variation range of the suspension parameters (GB/T 5599-1985:1985), the basic model of vehicle suspension parameter robust optimization can be expressed as follows:

$$\begin{cases} \min: W(C) = \sum_{i=1}^{n} \omega_i \phi(\|c - c_i\|) \\ \text{s.t.} \quad W - 2.75 \le 0 \\ \qquad 700 \le c_1 \le 1300 \\ \qquad 17.5 \le c_2 \le 32.5 \\ \qquad 107.8 \le c_3 \le 200.2 \\ \qquad 28 \le c_4 \le 52 \end{cases} \tag{1}$$

here $W(C) = \sum_{i=1}^{n} \omega_i \phi(\|c - c_i\|)$ is the surrogate model of vehicle vertical running stability, W is the vertical running stability index, and c_1, c_2, c_3 and c_4 respectively represent K_{pz}, C_{pz}, K_{sz}, and C_{sz}.

The signal-to-noise ratio is an important index used to evaluate the anti-jamming ability of robust optimization. In the present study, the smaller the value of the vertical running stability index, the more stable the running of the vehicle. This means that the mean μ and variance σ^2 of the vertical running stability index should be as small as possible. As the greater the signal-to-noise ratio η the more robust the output (Che et al., 2009) , the former was set as:

$$\eta = 1/(\mu^2 + \sigma^2) \tag{2}$$

Equation (3) is obtained by employing common logarithms to convert the signal-to-noise ratio η to the decibel value in Equation (2).

$$\eta = -10\lg(\mu^2 + \sigma^2) \tag{3}$$

On the basis of probability and statistics, $\mu^2+\sigma^2$ can be replaced by the unbiased estimates of the output function value, with the converted signal-to-noise ratio formula thus:

$$\eta = -10\lg(\frac{1}{n} W_i^2) \tag{4}$$

where W_i is the output value of the target function, i.e., the vertical running stability index.

As stated above, the greater the signal-to-noise ratio, the more robust the output. Therefore, the suspension parameter combination associated with the best robustness can be identified by comparing the signal-to-noise ratios of different test combinations.

Taguchi Robust Optimization of Suspension Parameters

The Taguchi method is based on experimental design aimed at improving the quality and robustness of a product (Yadav et al., 2010). The procedure employed here in the Taguchi robust optimization of vehicle suspension parameters is shown in Figure 2, and mainly involved the following steps:

(1) The multi-body dynamics simulation model of a rail vehicle is constructed in order to implement the simulation of vertical running stability.

(2) $C\{Kpz、Cpz、Ksz、Csz\}$, $N\{v、M、R\}$ are selected as the design parameters. The test sample points, utilized to construct the RBF surrogate model of vehicle vertical running stability, are calculated via the vehicle simulation model of vertical running stability.

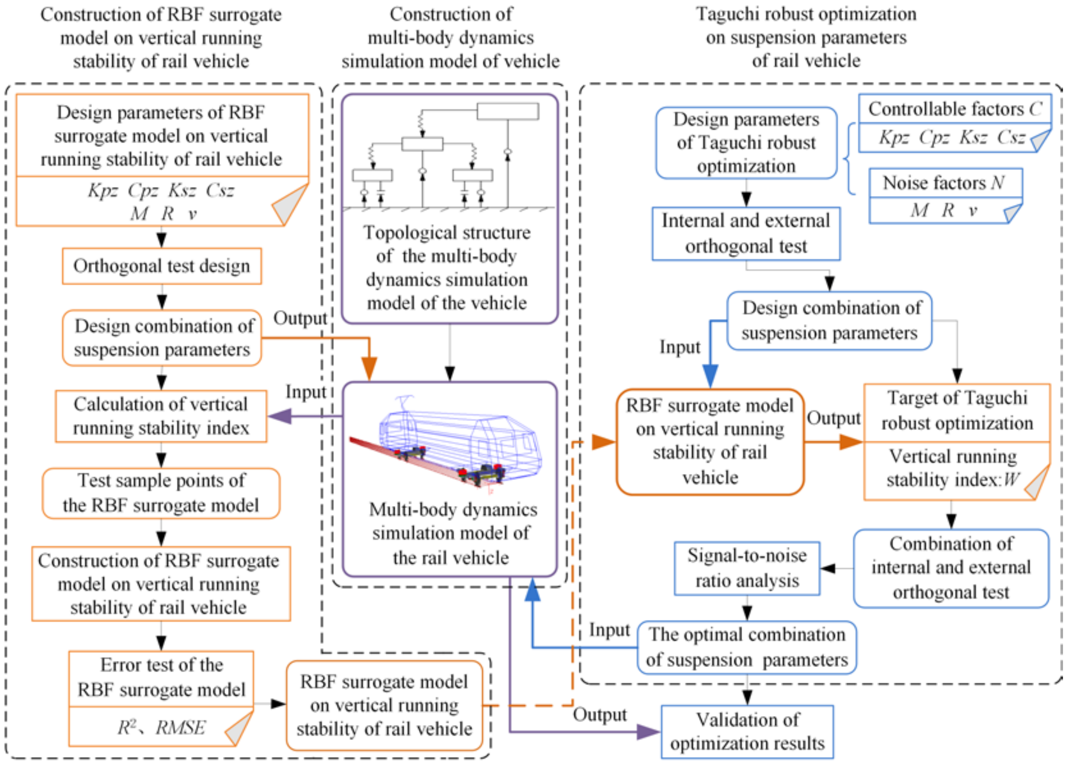

Fig. 2 The procedure of Taguchi robust optimization on suspension parameters

(3) $C\{Kpz、Cpz、Ksz、Csz\}$ are selected as the controllable factors of Taguchi robust optimization, and $N\{v、M、R\}$ are chosen as the noise factors. The vertical running stability index W of each design parameter combination is calculated through the RBF surrogate model of vehicle vertical running stability. Then the controllable factor combination, associated with the best robustness, is obtained via signal-to-noise ratio analysis.

(4) The optimal combination of controllable factors is simulated using the multi-body dynamics simulation model of the rail vehicle, and the variation in vertical running stability index W values is compared.

CONSTRUCTION OF DYNAMIC SIMULATION MODEL

Evaluation index of vehicle running stability

Vehicle running stability affects both vehicle running quality and passenger riding comfort. The Sperling Index is used worldwide as an index of vehicle running stability (Yan and Fu, 2012), and is formulated as follows :

$$W = 0.896\sqrt[10]{\frac{a^3}{f}\cdot F(f)} \qquad (5)$$

where a (unit: cm/s^2) is the vertical vibration acceleration of the car body, f (unit: Hz) is the vertical vibration frequency of the car body, and $F(f)$ is the modifying coefficient of the vibration frequency.

The modifying coefficient of the vibration frequency is expressed as shown in Equation (6) when calculating the vertical stability index:

$$F(f) = \begin{cases} 0.325f^2 & 0.5 < f < 5.9\text{Hz} \\ 400/f^2 & 5.9 < f < 20\text{Hz} \\ 1 & f > 20\text{Hz} \end{cases} \qquad (6)$$

The acceleration and frequency of vehicle vibration will change over time. When calculating vehicle stability, the vibration waveform should thus be grouped according to the vibration frequency, and the stability index W calculated according to the values of the different accelerations in each frequency group as follows:

$$W = \sqrt[10]{W_1^{10} + W_2^{10} + \cdots + W_N^{10}} \qquad (7)$$

where N is the total number of the frequency group.

Construction of multi-body dynamics model

Considering that the rail vehicle system is complex, this paper makes the following simplified and alternative to its research: (1) The model of rail vehicle vertical dynamics, as illustrated in Fig. 1, was abstracted into a topological structure composed of several rigid bodies, joints, and force elements. (2) Based on the laws of motion and relations between all the rigid bodies, the car body, bogie frame and wheel-sets were set in six degrees of freedom (6 DOF no W/R-Functon), as the linear motion along the z-axis and the rotation about the x-axis, the wheel-set can be set as six not-separate degrees of with two constraints (6 DOF W/R-Functon). (3) The connections between each two rigid bodies were simulated with equivalent force elements or constraints. The topological structure of the rail vehicle multi-body dynamics simulation model was constructed as indicated in Figure 3.

Referring to a certain type of high-speed rail vehicle, the main kinetic parameters are shown in Table 1. Based on the topological structure displayed in Fig. 3, the rail vehicle multi-body dynamics simulation model was built using the SIMPACK multi-body dynamics simulation software program, taking the German high interference track spectrum as the vertical track irregularity excitation. Here the suspension system is the key to constructing the simulation model. In this model the wheel-sets and bogie frame are connected by the primary suspension, as well as the vertical damping facilities and axle box positioning devices, with the frame and car body connected by the secondary suspension, as well as vibration damping components such as anti-yaw

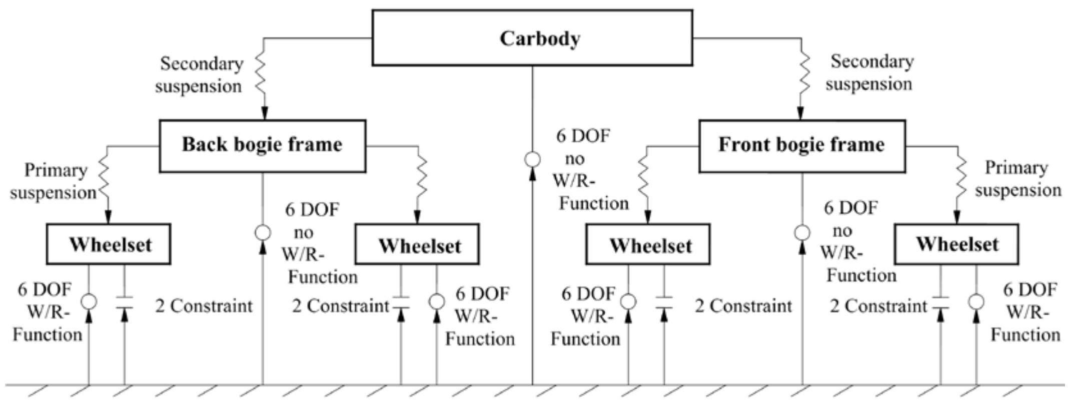

Fig. 3 The topological structure of the multi-body dynamics simulation model of rail vehicle

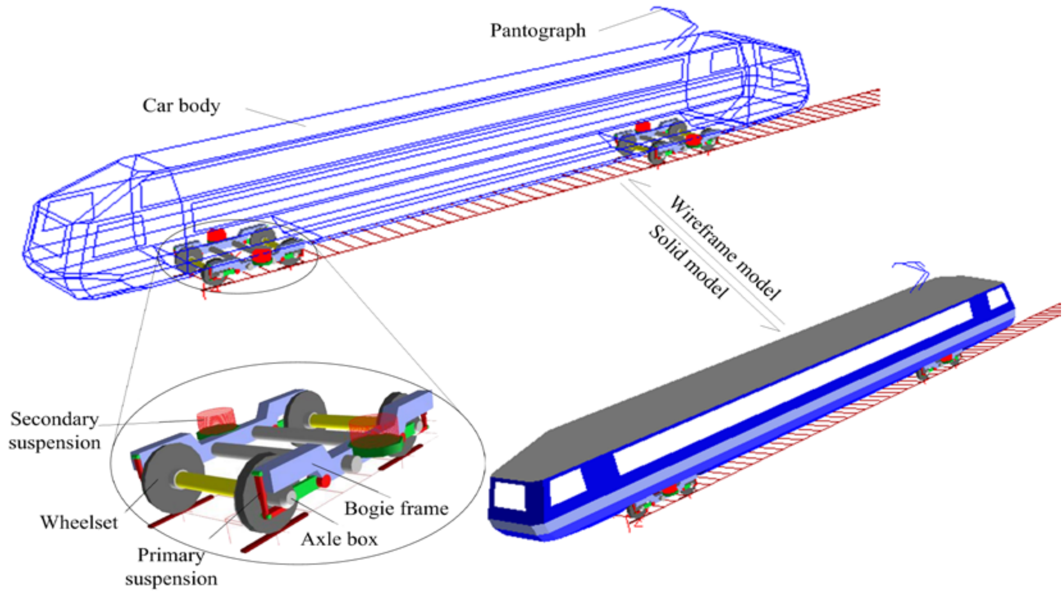

Fig. 4 The multi-body dynamics simulation model of rail vehicle

damping, lateral damping, and vertical damping. Spring and damping were abstracted into force elements containing three-dimensional stiffness and vertical damping in SIMPACK. Therefore, in the model the primary suspension is replaced by four sets of compact force elements, and the secondary suspension is replaced by six sets of compact force elements. The multi-body dynamics simulation model of the rail vehicle is shown in Figure 4.

Table 1 The main kinetic parameters of a certain type of high-speed rail vehicle

Parameters	Value	Units
Half distance between bogie centers (L_c)	17500	mm
Wheelbase of bogie (L_w)	2500	mm
Wheel rolling circle diameter	860	mm
Car body mass (m_c)	32.5	t
Bogie mass (m_{b1}/ m_{b2})	2.56	t
Wheelset mass (m_{w1}/ m_{w2}/ m_{w3}/ m_{w4})	2.08	t
Car body nod movement of inertia (I_c)	1500.8	t·m^2
Bogie nod movement of inertia (I_{b1}/ I_{b2})	1.405	t·m^2
Vertical displacement of car body (Z_c)	---	---
Vertical displacement of bogie (Z_{b1}/ Z_{b2})	---	---
Random rail irregularities (Z_{w1}/ Z_{w2}/ Z_{w3}/ Z_{w4})	---	---
Vertical stiffness of primary suspension (K_{pz})	1000	kN/m
Vertical damping of primary suspension (C_{pz})	25.0	kN·s/m
Vertical stiffness of secondary suspension (K_{sz})	154	kN/m
Vertical damping of secondary suspension (C_{sz})	40	kN·s/m

Simulation of Vehicle Running Stability Based on the Multi-body Dynamics Simulation Model

The vertical running stability W can be calculated based on the simulation process for vehicle running stability shown in Figure 5 via the multi-body dynamics simulation model. To determine the quantitative relations between W and the suspension parameters K_{pz}, C_{pz}, K_{sz}, and C_{sz}, the suspension parameters in the system file (.sys) of the multi-body dynamics simulation model were parameterized, with the parsing and replacement methods then introduced to substitute the corresponding suspension parameters, and the new (.sys) file used for simulation. Finally, the vertical running stability W was calculated through the analysis, time-domain integration and filtering processing of the vehicle dynamic performance results.

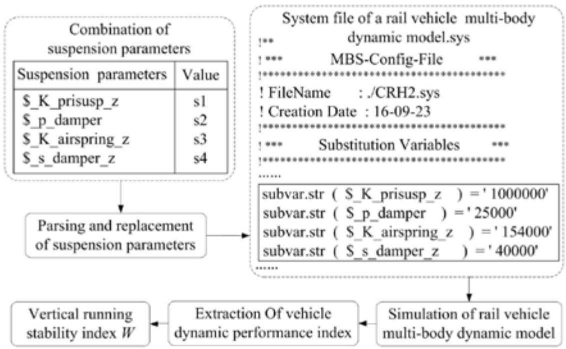

Fig. 5 Simulation process for vehicle running stability

CONSTRUCTION OF RBF SURROGATE MODEL OF VERTICAL RUNNING STABILITY

Basic Form of the RBF Surrogate Model

The RBF surrogate model is also known as the Radial Basis Function surrogate Model. In this model the Euclidean distance between the point to be measured and the sample point is used as the independent variable, with the complex multi-dimensional problem transformed into a one-dimensional problem by calculating the response value of the point to be measured via linear weighting (Shi et al., 2016).

The RBF surrogate model, which possesses firm function approximation ability, faster convergence speed and higher accuracy, offers a convenient method with which to deal with the non-linear relationship between design parameters and target responses. Therefore, in order to obtain values of the vehicle running stability index quickly and accurately, the dynamic simulation model of vertical running stability is here replaced by the RBF surrogate model.

The mathematical formula of the RBF surrogate model can be described as follows in Equation (8):

$$W(C)=\sum_{i=1}^{n}\omega_i\phi(\|x-x_i\|) \tag{8}$$

where ω_i is the weight coefficient, $\phi(\|x-x_i\|)$ is the selected as-radial basis function, and $||x\text{-}x_i||$ is the Euclidean distance between point x and the ith sample point x_i.

Typically, the commonly used radial basis function are shown as follows:

Gaussian basis function:

$$\phi(\|x-x_i\|)=e^{(-\|x-xi\|^2/c^2)} \tag{9}$$

Multi-quadratic basis function:

$$\phi(\|x-x_i\|)=(\|x-x_i\|^2+c^2)^{\frac{1}{2}} \tag{10}$$

Reciprocal multi-quadratic basis function:

$$\phi(\|x-x_i\|)=(\|x-x_i\|^2+c^2)^{-\frac{1}{2}} \tag{11}$$

where c is a given real number greater than zero.

When Eq. (8) is applied to prediction, the following interpolation conditions must be satisfied:

$$Y(x_i)=W(x_i) \tag{12}$$

where i is the number of sample points from 1 to n, $Y(x_i)$ is the predicted response value, and $W(x_i)$ is the precise output value.

Substituting Equation (12) into Eq. (8), Equations (13) and (14) can be obtained as follows:

$$\boldsymbol{\varphi}\cdot\boldsymbol{\omega}=\mathbf{W} \tag{13}$$

$$\boldsymbol{\varphi}=\begin{bmatrix}\phi(r_{11}) & \cdots & \phi(r_{1n})\\ \vdots & \cdots & \vdots\\ \phi(r_{31}) & \cdots & \phi(r_{nn})\end{bmatrix} \tag{14}$$

where $\boldsymbol{\omega}=[\omega_1,\cdots,\omega_n]^T$ is the vector consisting of weight coefficients, $r_{ij}=\|x_i-x_j\|$ $(i,j=1,\cdots,n)$ is the Euclidean distance formed by the sample points, and $\mathbf{W}=[W_1,\cdots,W_n]^T$ is a vector composed of the output values calculated by the dynamic simulation model.

After the determination of the design parameters, the test sample points were obtained from the experimental design, with the precise values of the sample points then obtained by simulation in the dynamic simulation model of the vertical running stability. The RBF surrogate model of vehicle vertical running stability can be constructed by selecting the radial basis function $\phi(\|x-x_i\|)$ and using Eqs. (13) and (14) to calculate the weight coefficient $\boldsymbol{\omega}$.

Orthogonal Experimental Design of Suspension Parameter

Multiple groups of suspension parameter sample points must be built using the experimental design method in the process of modeling the RBF surrogate model of vehicle vertical running stability. The orthogonal experiment design method (Huang et al., 2004), which has the advantages of reduced testing times and even distribution of data, can be used to solve both multi-factor and multi-level coefficient problems. Therefore, the orthogonal experiment design method was here employed in order to determine the sample points of the RBF surrogate model, with $C\{K_{pz}、C_{pz}、K_{sz}、C_{sz}\}$ and $N\{v、M、R\}$ selected as the design parameters in carrying out the experimental design.

Three levels were selected for each of the suspension parameters K_{pz}, C_{pz}, K_{sz}, and C_{sz}: level 2, which represents the initial values of the design parameters; and level 1 and level 3, which respectively represent a variation of ± 20% of the initial value. Three levels were also employed for passenger capacity M - no load, half load, and full load - to simulate the change in passenger capacity during vehicle running. Similarly, and according to the design standard for the curve radius of a high-speed passenger line (Zhu and Yi, 2011), the railway curve radius R was set to 6 km, 7 km, and 8 km. Since the object of the present paper is a high-speed vehicle travelling at a speed of 300 km/h, the vehicle speed v was selected in the range of 200 to 300 km/h.

The design parameters and their level values are summarized in Table 2.

Table 2 Design parameters and their level values

Parameters	K_{pz}	C_{pz}	K_{sz}	C_{sz}	v	M	R
Units	kN/m	kN·s/m	kN/m	kN·s/m	km/h	kg	km
Level 1	800	20	123.2	32	200	no	6
Level 2	1000	25	154	40	250	half	7
Level 3	1200	30	184.8	48	300	full	8

According to the numbers and levels of the design parameters, an orthogonal array of L27(3^7) was constructed. The dynamic simulation of 27 sets of parameters was then carried out by the dynamic simulation model of vertical running stability, thereby obtaining values of the vertical running stability index W for each parameter combination, as shown in Table 3.

Table 3 Test sample of the RBF surrogate model on vertical running stability

Test number	Design parameters							Sample value
	Kpz	*Cpz*	*Ksz*	*Csz*	*v*	*M*	*R*	*W*
T1	1	1	1	1	1	1	1	2.025
T2	1	1	1	1	2	2	2	2.242
T3	1	1	1	1	3	3	3	1.989
T4	1	2	2	2	1	1	1	2.078
T5	1	2	2	2	2	2	2	2.296
T6	1	2	2	2	3	3	3	1.769
T7	1	3	3	3	1	1	1	2.211
T8	1	3	3	3	2	2	2	2.223
T9	1	3	3	3	3	3	3	2.247
T10	2	1	2	3	1	2	3	2.016
T11	2	1	2	3	2	3	1	2.054
T12	2	1	2	3	3	1	2	2.146
T13	2	2	3	1	1	2	3	2.374
T14	2	2	3	1	2	3	1	1.941
T15	2	2	3	1	3	1	2	2.281
T16	2	3	1	2	1	2	3	2.054
T17	2	3	1	2	2	3	1	1.857
T18	2	3	1	2	3	1	2	2.080
T19	3	1	3	2	1	3	2	1.996
T20	3	1	3	2	2	1	3	1.952
T21	3	1	3	2	3	2	1	1.743
T22	3	2	1	3	1	3	2	2.038
T23	3	2	1	3	2	1	3	1.976
T24	3	2	1	3	3	2	1	1.788
T25	3	3	2	1	1	3	2	2.116
T26	3	3	2	1	2	1	3	2.147
T27	3	3	2	1	3	2	1	2.119

The RBF Surrogate Model of Vertical Running Stability

The reciprocal multi-quadratic basis function shown in Equation (11) was used as the radial basis function, take c = 1.

Since Eq. (13) does not overlap at the sample points and the radial basis function $\phi(\|x - x_i\|)$ is a positive definite function, the weight coefficient **w** has a unique solution, as illustrated in Equation (15):

$$\boldsymbol{\omega} = \boldsymbol{\varphi}^{-1} \cdot \mathbf{W} \qquad (15)$$

The weight coefficient **ω** can be calculated via Eqs. (13), (14) and (15) using the test sample value *W* of the RBF surrogate model of vertical running stability shown in Table 3.

ω=[2.0238 2.2406 1.9878 2.0767 2.2945 1.7677 2.2098 2.2215 2.2458 2.0145 2.0527 2.1447 2.3726 1.9397 2.2797 2.0526 1.8558 2.0788 1.9934 1.9507 1.7401 2.0369 1.9749 1.7867 2.1147 2.1458 2.1175]^T 。

The RBF surrogate model of vehicle vertical running stability could then be constructed by substituting weight coefficient **ω** into Eq. (8), which obtains the response value of the point to be measured.

Error Testing of the RBF Surrogate Model of Vertical Running Stability

To test the fitting precision of the RBF surrogate model of vertical running stability, the coefficient of determination R^2 and the root mean square *RMSE* were adopted to determine the fitting error (Qiu et al., 2016). The coefficient of determination R^2 and the root mean square *RMSE* can be expressed as in Equation (16) and Equation (17) as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=0}^{m}(y_i - \hat{y}_i)^2} \qquad (16)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \qquad (17)$$

where *m* is the number of sample points obtained to test the fitting precision of the RBF surrogate model, y_i is the output value of the *i*th sample point calculated by the dynamic simulation model, $\bar{y}$ is the average output value of the sample points, and $\hat{y}_i$ is the response value of the surrogate model of vehicle running stability at the *i*th sample point.

Values of R^2 closer to 1 and *RMSE* closer to 0 indicate that the fitting degree of the surrogate model is better and that the precision is higher.

Ten sets of vertical running stability index values *W* were randomly selected from Table 3, calculated based on the dynamic simulation model of vertical running stability as the error test sample. These 10 sets of sample points were then substituted into the constructed RBF surrogate model to obtain the corresponding vertical running stability index. In this case the coefficient of determination R^2 of the RBF surrogate model of vertical running stability was 0.982, and the root mean square *RMSE* was 0.073, calculated according to Eqs. (16) and (17), respectively. These values indicate that the fitting error of the RBF surrogate model is suitably small, and that the RBF surrogate model of vertical running stability could be used to fit the running stability analysis results obtained via the dynamic simulation model of rail vehicle vertical running stability.

TAGUCHI ROBUST OPTIMIZATION OF SUSPENSION PARAMETERS

Factor classification and levels

In order to improve the vertical running stability of the vehicle under the influence of the noise factors. $C\{K_{pz}$、C_{pz}、K_{sz}、$C_{sz}\}$ were selected as the controllable factors, with each factor characterized by 4 levels whose interval varied by ±30% from the initial value. Similarly, $N\{v$、M、$R\}$ were selected as the noise factors with which to optimize the suspension parameters. In this case, three levels were set for passenger capacity *M* of no load, half load and full load, while the railway curve radius R was set at 6 km, 7 km, 8 km, and 9 km. Finally, the vehicle speed v was assigned four levels ranging from 180 to 300 km/h. All factors and their levels are summarized in Table 4.

Table 4 Factors and their levels

Factors	Parameters	Units	Level 1	Level 2	Level 3	Level 4
Control lable factors	K_{pz}	kN/m	700	900	1100	1300
	C_{pz}	kN·s/m	17.5	22.5	27.5	32.5
	K_{sz}	kN/m	107.8	138.6	169.4	200.2
	C_{sz}	kN·s/m	28	34	46	52
Noise factors	M	kg	no	half	full	
	R	km	6	7	8	9
	v	km/h	180	220	260	300

Experimental design and optimization results

An orthogonal array of $L_{16}(4^4)$ was selected to represent the controllable factors, with one of $L_{16}(3^1*4^2)$ representing the noise factors in the experimental design. According to the internal array of controllable factors and the external array of noise factors, an internal and external orthogonal test table was constructed and a total of 16 * 16=256 simulations were carried out. Values of the vertical running stability index W, mean value μ and signal-to-noise ratio η of each group were calculated through the RBF surrogate model of vertical running stability. The orthogonal test table and calculation results are shown in Table 5, and the trend of the mean value μ and the signal-to-noise ratio η of the 16 tests is shown in Figure 6.

It can be seen from Fig. 6 that the signal-to-noise ratio η of test T9 is the highest among the 16 tests. Thus, the robustness of suspension parameter combination T9 is the best according to the principle that the greater the signal-to-noise ratio, the more robust the output. And the mean value μ of the vertical running stability index is the smallest among the 16 tests, which indicates that the vertical running stability of the vehicle under T9 is optimal.

A comparison of vertical running stability index values for initial and optimized suspension parameters is shown in Table 6.

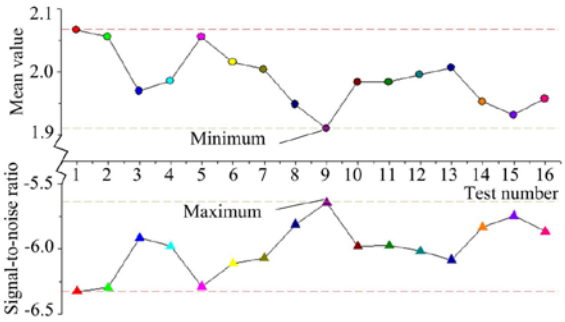

Fig. 6 Trend of the mean value and the signal-to-noise ratio

Table 6 Mean value of W and suspension parameters of initial and optimized versions

Items	Kpz (kN/m)	Cpz (kN·s/m)	Ksz (kN/m)	Csz (kN·s/m)	Mean value of W
Non-optimized	1000	25	154	40	2.067
Optimized	1100	17.5	169.4	52	1.911
Percentage (%)	10	30	10	30	7.55

Analysis of Table 6 reveals that the vertical running stability index is improved by 7.55% from 2.067 to 1.911 under the different running conditions, indicative of a considerable improvement due to robust optimization.

Table 5 Orthogonal experiment and results

Internal array / External array																							
					M	1	2	3	1	1	2	3	1	1	2	3	1	1	2	3	1	Mean μ	Signal -to -noise Ratio η
					v	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4		
					R	1	2	3	4	1	3	2	4	1	2	3	4	1	2	3	4		
Test	K_{pz}	C_{pz}	K_{sz}	C_{sz}																			
*T*1	1	1	1	1		1.90	1.88	2.20	2.04	1.89	2.12	2.19	1.93	1.89	2.07	2.09	2.24	1.97	2.27	2.23	2.16	2.067	-6.325
*T*2	1	2	2	2		2.27	1.95	2.23	1.72	2.05	2.23	1.93	1.75	2.26	2.00	1.96	2.29	1.85	2.29	2.05	2.07	2.056	-6.296
*T*3	1	3	3	3		1.90	1.87	2.24	1.94	1.89	1.83	1.86	2.08	1.82	2.10	2.07	1.78	1.99	1.98	1.83	2.34	1.970	-5.916
*T*4	1	4	4	4		2.33	2.03	2.16	2.08	1.83	1.92	1.94	2.01	1.98	2.02	1.96	2.04	1.77	1.95	1.92	1.84	1.986	-5.979
*T*5	2	1	2	3		2.18	2.00	2.14	2.17	2.05	1.94	1.90	2.35	1.92	2.01	1.77	2.17	2.00	2.33	1.84	2.13	2.056	-6.288
*T*6	2	2	1	4		2.17	1.86	1.87	1.93	2.29	2.00	1.93	2.03	1.97	2.24	1.87	1.82	2.00	2.16	2.06	2.06	2.016	-6.111
*T*7	2	3	4	1		2.31	1.80	1.94	2.17	1.79	1.80	1.82	1.92	2.09	2.10	2.05	1.78	1.98	2.26	2.24	2.01	2.004	-6.070
*T*8	2	4	3	2		1.84	2.08	2.04	2.00	1.91	2.18	1.82	2.01	2.15	1.90	1.78	2.03	1.92	1.90	1.79	1.83	1.949	-5.812
T9	3	1	3	4		1.84	1.81	1.83	1.76	1.94	1.78	2.17	2.00	1.96	1.77	1.98	1.91	2.23	1.80	1.93	1.86	1.911	-5.644
*T*10	3	2	4	3		1.97	1.92	1.72	2.15	1.78	1.88	2.09	2.02	1.74	2.16	1.98	2.00	1.96	1.83	2.30	2.24	1.984	-5.980
*T*11	3	3	1	2		1.95	1.79	1.87	2.19	2.01	2.02	2.34	2.06	1.85	2.03	1.80	1.93	1.94	2.13	1.93	1.91	1.984	-5.974
*T*12	3	4	2	1		1.98	2.09	1.90	2.12	1.87	2.19	1.93	2.08	1.94	2.10	1.94	2.03	1.75	2.21	1.85	1.95	1.996	-6.018
*T*13	4	1	4	2		2.33	1.80	1.86	1.87	2.27	2.25	1.80	1.78	1.95	2.01	2.04	1.90	1.99	1.87	2.18	2.21	2.007	-6.085
*T*14	4	2	3	1		1.83	1.85	1.81	2.03	1.86	2.24	2.13	1.89	1.89	1.84	2.08	2.02	1.80	2.06	2.07	1.85	1.953	-5.834
*T*15	4	3	2	4		2.13	1.73	1.78	1.82	1.83	1.98	1.81	1.76	1.96	1.83	2.33	1.89	2.12	1.99	2.00	1.95	1.932	-5.748
*T*16	4	4	1	3		1.75	2.05	2.05	1.86	1.80	1.83	1.86	1.79	1.87	1.74	2.17	1.90	2.31	2.09	2.21	2.04	1.958	-5.867

Table 7 Combination of running conditions and vertical running stability index comparison

Conditions	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16
M	1	2	3	1	1	2	3	1	1	2	3	1	1	2	3	1
v	1	1	1	1	2	2	2	2	3	3	3	3	4	4	4	4
R	1	2	3	4	1	3	2	4	1	2	3	4	1	2	3	4
Non-optimized	1.90	1.76	2.24	2.04	1.89	2.02	2.10	1.93	1.81	1.97	2.09	2.04	1.87	2.17	2.13	2.16
Optimized	1.84	1.81	1.83	1.77	1.94	1.78	2.01	1.87	1.96	1.78	2.06	1.91	2.03	1.80	1.93	1.86

VALIDATION OF TAGUCHI OPTIMIZATION RESULTS

As displayed in Table 7, in order to verify the effect of Taguchi robust optimization of the suspension parameters, 16 types of vehicle running conditions were obtained according to the test order of the external array of noise factors shown in Table 4. Values of the non-optimized and optimized vertical running stability indexes were then compared for each of the 16 types of different vehicle running conditions, with the initial and optimized suspension parameters entered into the dynamic simulation model of vertical running stability to calculate the dynamic performance of the rail vehicle. A summary of the comparison of vertical running stability index is shown in Figure 7.

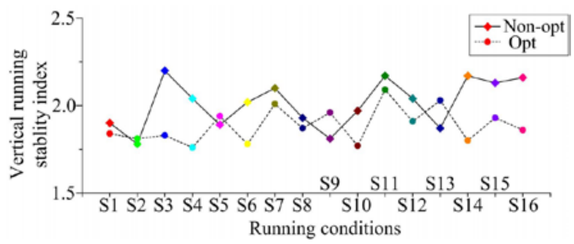

Fig. 7 Comparison of vertical running stability index

It can be seen in Fig. 7 that under most running conditions, values of the optimized vertical running stability index are lower than those obtained prior to optimization. And the amplitude of the vertical running stability index over the whole interval is 0.42, while 0.29 after optimization, which is reduced by 31.0%.

Under running condition S3, the robust optimization effect is the most obvious, with the difference between the non-optimized and optimized versions of the vertical running stability index equal to 0.37. However, under the conditions of S2, S5, S9 and S13, the vertical running stability index is a little worse than before optimization, but all of them are within the optimum evaluation grade of vertical running stability of rail vehicle in China.

Running condition S11 is defined as a full-loaded state, whose railway curve radius is equal to 8 km and running speed 260 km/h. As S11 is the most similar of all the tested conditions to the actual running situation of high-speed rail vehicles, the suspension parameters of the non-optimized and optimized versions were input into the dynamic simulation model of vertical running stability for this condition. The time domain graph of the vertical acceleration comparison is shown in Figure 8, the amplitude of the vertical acceleration is clearly in decline.

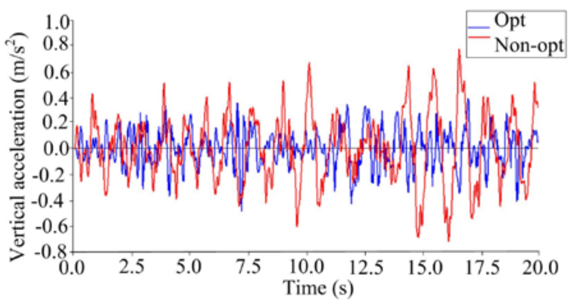

Fig. 8 Comparison of the vertical acceleration in S3

Under running condition S11, the speed, railway curve radius and passenger capacity were changed and then inputed into the dynamic simulation model of vertical running stability for simulation and analysis, a comparison of the vertical running stability index values under different noise factors is shown in Figure 9.

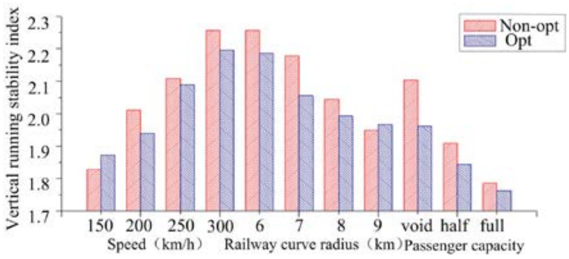

Fig. 9 Comparison of vertical running stability indexes under the influence of noise factors

It can be seen from Fig. 9 that the vertical running stability index gradually increases with an increase in vehicle speed, with the fluctuation amplitude across the whole interval smaller than that obtained prior to parameter optimization. In contrast, an increase in the railway curve radius and passenger capacity results in a gradual decrease in the vertical running stability index, although the fluctuation amplitude of the vertical running stability is again smaller than that observed before the optimization of the suspension parameters.

In summary, the above analyses have proven that vehicle robustness can be significantly improved after Taguchi robust optimization of suspension parameters, thus validating the effectiveness of this method.

CONCLUTIONS

In this paper, an RBF surrogate model of high-speed rail vehicle vertical running stability was established. The suspension parameter combination associated with the best robustness under the influence of selected noise factors was then obtained via the Taguchi robust optimization method, leading to an obvious improvement in the vertical running stability of the vehicle under different running conditions. The following concrete conclusions can be drawn:

(1) The control factors and noise factors associated with the running process of a rail vehicle were determined, enabling the subsequent establishment and design of a robust optimization model and scheme for the vehicle suspension parameters.
(2) A multi-body dynamics simulation model of the vertical running stability of the rail vehicle and its suspension system was established based on the vertical dynamic model, with the vertical running stability of the vehicle then calculated through the established model.
(3) A test sample for the RBF surrogate model was obtained via the orthogonal experiment design method, with the RBF surrogate model of the vertical running stability model constructed based on the simulation of the multi-body dynamics simulation model.
(4) Vertical stiffness and vertical damping of the primary and secondary suspensions were taken as the controllable factors, and speed, passenger capacity and railway curve radius selected as the noise factors based on the Taguchi method. Vertical running stability index values under different running conditions were then calculated using the RBF surrogate model. The suspension parameter combination associated with the best robustness under the influence of the noise factors was obtained according to the principle of the greater the signal-to-noise ratio, the more robust the output.
(5) Dynamic simulation of the non-optimized and optimized suspension parameters was carried out using the dynamic simulation model of vertical running stability under different running conditions. After optimization, the mean value of the vertical running stability index was improved by 7.55% and the amplitude of the vertical running stability index over the whole range was reduced by 31.0%, vehicle robustness was improved significantly.
(6) The traditional optimization method only considers the influence of suspension parameters on vehicle running performance, and the suspension parameters optimization results are different under different running conditions. Compared with the traditional optimization method, the method proposed in this paper considered noise factors and multiple running conditions, the optimization results can be applied to a variety of running conditions, vehicle robustness was improved significantly, thus validating the effectiveness of the proposed method.

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面向垂向運行平穩性的高速軌道車輛懸掛參數穩健優化

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摘要

考慮雜訊因數對高速軌道車輛垂向運行平穩性的影響，對懸掛參數進行穩健優化可以提高車輛在不同運行工況條件下的抗干擾性，保證車輛運行品質。引入田口穩健優化方法，以一、二系垂向剛度、阻尼為可控因數，以車速、載客量及軌道曲線半徑為雜訊因數，構建懸掛參數穩健優化設計基本模型。利用徑向基代理模型非線性擬合的優勢，構建車輛垂向運行平穩性徑向基代理模型，精確分析可控因數和雜訊因數對車輛垂向運行平穩性的影響。在此基礎上，通過對可控因數和雜訊因數進行內外正交試驗和信噪比分析，獲得在雜訊因數影響下穩健性最優的懸掛參數組合。算例表明，對懸掛參數進行穩健優化後，在不同行駛工況下車輛的垂向運行平穩性指標均值比優化前提高了 7.55%，且優化後車輛垂向運行平穩性指標在整個區間的波動幅度較優化前降低了 31.0%，顯著提高了車輛的穩健性。