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Robust Optimization for Suspension Parameters of Suspended Monorail Vehicle Using Taguchi Method and Kriging Surrogate Model

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Keywords： Robust optimization, Surrogate mode, Suspended monorail vehicle, Taguchi method.

ABSTRACT

This study proposes an effective method to robust optimize the vehicle suspension parameters. To implement this method, firstly, a multi-body dynamics model of the suspended monorail vehicle was constructed as a simulation model to obtain the vehicle running stability index. Then, the multi-combination suspension parameters obtained by the orthogonal experimental design method are brought into the simulation model to obtain the training samples of the surrogate model, and the Kriging surrogate model on the vehicle running stability is constructed. Finally, the Taguchi method is used to find the optimal combination of suspension parameters based on the Kriging surrogate model, and the running stability index values of the suspension parameters corresponding to the initial and optimal combinations is compared. The results show that the robust optimization method proposed in this paper improves the lateral and vertical running stability of suspended monorail vehicle by 10.08% and 9.18%, respectively.

INTRODUCTION

The suspended monorail system is an environmentally friendly transit system, which originated from Wuppertal and further developed in system is moving at the track beams, and the track beams are erected by the upright column in the air. The design of this special system has a separate right of way, which can alleviate the traffic congestion and reduces frequent traffic accidents (Li et al., 2015; Bao et al., 2016). Furthermore, it has the advantages of high adaptability, safety and the environmental protection, can be as a supplement to the public transportation in large cities. Due to these various advantages, the suspension monorail system is developing in China and other countries, and the first suspension monorail traffic line using lithium battery as power has been built in China (Yunta et al., 2016).

As a special urban transit system, the suspension monorail vehicle can be driven in the short radius curve and provide more spatial adaptability for the public transportation system in the small and medium-sized cities. However, due to the special structure of vehicles and the characteristics of traffic routes, the dynamic performance of the suspension monorail vehicle is very susceptible to the impact of uncertainty factors under complex operating conditions (e.g. the mixed operating conditions of straight track and curved track). These uncertainty factors (for example, but not limited to, the vehicle speed and the force of crosswind) cause irregular vibration of the vehicle, leading to degradation of dynamic performance like running stability (Sim et al., 2014). Therefore, it is necessary to fully consider the uncertainty factors that cause the performance change in the optimization of the suspension monorail vehicle.

The uncertainty-based optimization theory was first proposed by Dantzig in 1955 (Dantzig, 1955). The effective implementation of this theory is based on an optimization model containing uncertainty factors, and the uncertainty input on the output response is considered comprehensively. Among them, the robust design optimization method is widely accepted as a promising uncertainty-based optimization method, which can not only obtain a robust output response, but also maintain the insensitivity to uncertainty input when subjected to variations (Chen et al., 1996 1997). At present, the approach about robust design optimization method of suspended monorail vehicle is few, and most research literature applies the simulation-based design methods (Meisinger, 2009; Li et al. 2015; Gutarevych, 2015).

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However, the simulation-based design methods have some shortcomings when it comes to practical engineering complex systems, such as high time consuming, limited accuracy and low efficiency, etc.

Given this background, a robust optimization strategy was proposed for suspension parameters of suspended monorail vehicle to improve the running stability of vehicle under multiple operating conditions. In this strategy, the combination of Kriging surrogate model and Taguchi method realizes the robust optimization for the suspension parameters of suspension monorail vehicle and obtains the robust running stability index under the impact of uncertainty factors. The paper is organized as follows. The multi-body dynamics model of suspended monorail vehicle is constructed in Section 2. The Kriging surrogate model for running stability of suspended monorail vehicle is established and the fitting deviation of the model is tested in Section 3. The results of Taguchi robust optimization based on the Kriging surrogate model and related discussion are shown in Section 4. Finally, the conclusions and future work are presented in Section 5.

MULTIBODY DYNAMICS MODEL OF SUSPENDED MONORAIL VEHICLE

Construction of suspended monorail vehicle model

In order to construct the multi-body dynamics model of the suspended monorail vehicle, a certain type of suspended monorail vehicle is used as the model basis for the multi-body dynamics model. Fig.1 is the schematic diagram of a certain type of suspended monorail vehicle.

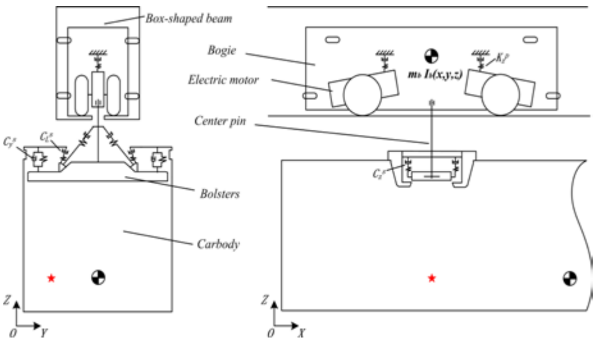

Fig. 1. The schematic diagram of suspended monorail vehicle.

Considering the complexity of the suspension monorail system, this paper makes the following simplification and substitution for its research: (1) The schematic diagram of suspension monorail vehicle, as illustrated in Fig. 1, was abstracted into a topological structure composed of several rigid bodies, joints, and force elements. (2) The connections between each two rigid bodies were simulated with equivalent force elements or constraints. The topological structure for multi-body dynamics model of suspended monorail vehicle was constructed as indicated in Fig. 2.

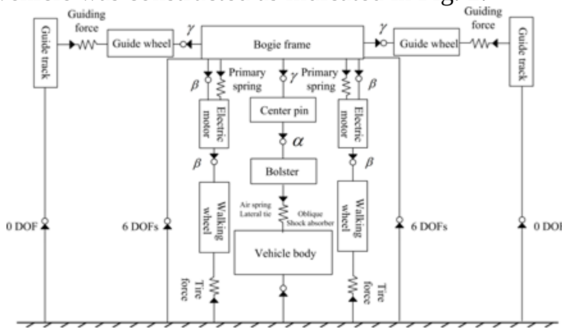

Fig. 2. The topological structure of suspended monorail vehicle.

Based on the topological structure displayed in Fig. 2, the multi-body dynamics model of suspended monorail vehicle was built using the Adams software. Considering the characteristics of the rubber type of the suspended monorail vehicle, the research method of the power spectral density of A-level stochastic road roughness is used to model and analyze the track beam roughness of the suspended monorail system, and the A-level stochastic road surface simulation diagram is shown in Fig. 3 (GB 7031, 1986). The multi-body dynamics model of suspended monorail vehicle is shown in Fig. 4. The accuracy of the model of suspended monorail vehicle was verified in the author's master thesis (Liu, 2017).

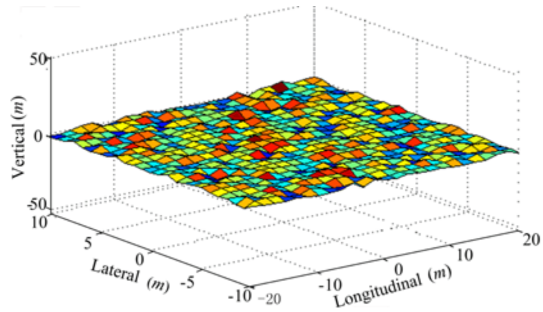

Fig. 3. A-level stochastic road surface simulation diagram.

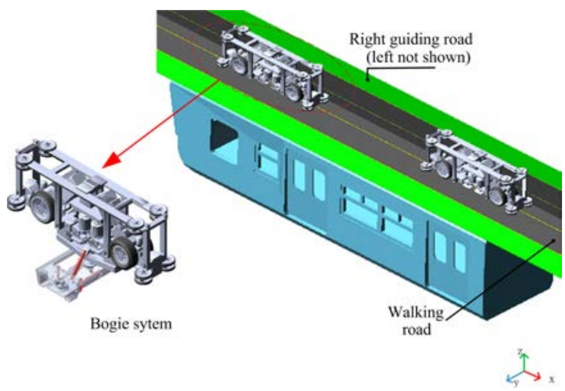

Fig. 4. The multi-body dynamics model of suspended monorail vehicle.

Running stability simulation-based on multi-body

dynamics model

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 (Wang, 1994). The evaluate an expression of running stability as follows:

$$W = 0.896\sqrt[10]{\frac{a^3}{f}\cdot F(f)}\,. \tag{1}$$

where f (Hz) is the vibration frequency of the vehicle body, F(f) is the modifying coefficient of the vibration frequency, and a (cm/s^2) is the acceleration of the car body, wherein, The mounting position of acceleration measuring device is shown in the red dot (☆) in Fig. 1, which below the vertical center of the bogie frame, and 1000mm from the longitudinal symmetrical surface of the vehicle body

CONSTRUCTION OF SURROGATE MODEL ON THE VEHICLE RUNNING STABILITY

Basic Form of the Kriging method

The Kriging method is also known as the spatial interpolation method, which is based on the theoretical and structural analysis of the variation function and a method for the optimal unbiased estimation of regional change in the finite region (Krige, 2015; Oliveira et al., 2013; Yang, 2016). A typical Kriging surrogate model algorithm form as shown in Eq. (2):

$$y(X) = f(X) + Z(X)\,, \tag{2}$$

where y(X) is the Kriging surrogate model, f(X) is the constant term of the global estimate design space. Z(X) is the results of the random process, which determines the local deviation. The variance is σ_Z^2 and the covariance is:

$$\mathrm{cov}[Z(x_i), Z(x_j)] = \sigma_Z^2[R_{ij}(\theta, x_i, x_j)]\,, \tag{3}$$

where x_i and x_j denotes two points of training samples, $[R_{ij}(\theta, x_i, x_j)]$ is the correlation function with θ, which is used to describe the relationship between x_i and x_j. As the relationship between any two sample points is related to their distance, the correlation function can be written as below:

$$R(\theta, x_i, x_j) = \prod_{k=1}^{n} R_k(\theta_k, d_k),\;\; d_k = \left|x_i^k - x_j^k\right|, \tag{4}$$

where n is the number of design variables and x_i^k and x_j^k are the corresponding k-th components of x_i and x_j in the training sample.

The Gaussian function used in engineering applications is the correlation function $R_k(\theta_k, d_k)$, whose mathematical expression as follows:

$$R_k(\theta_k, d_k) = \exp(-\theta_k d_k^2)\,, \tag{5}$$

When the correlation function $R_k(\theta_k, d_k)$ is determined. Then, we have

$$\hat{y}(x) = f(x)^T\hat{\beta} + r^T(x)R^{-1}(y - F\hat{\beta})\,, \tag{6}$$

where $f(x) = [f_1(x), f_2(x), \ldots, f_k(x)]^T$, $y = [y_1, y_2, \ldots, y_m]^T$, $r^T(x) = [R(x, x_1), R(x, x_2), \ldots, R(x, x_m)]$,

$$R = \begin{bmatrix} R(x_1, x_1) & \cdots & R(x_1, x_m) \\ \vdots & \ddots & \vdots \\ R(x_m, x_1) & \cdots & R(x_m, x_m) \end{bmatrix},\quad F = \begin{bmatrix} f^T(x_1) \\ \vdots \\ f^T(x_m) \end{bmatrix},$$

According to the above equations, we can derive:

$$MLE = \max_{\theta_k > 0}\left\{-\frac{1}{2}\left[n\ln(\sigma_Z^2) + \ln(|R|)\right]\right\}, \tag{7}$$

where the variance estimate can be calculated by Eq.(8) :

$$\sigma_Z^2 = \frac{1}{m}(y - F\hat{\beta})^T R^{-1}(y - F\hat{\beta})\,. \tag{8}$$

The training samples and experimental design

Multiple groups of test sample points need to be built using the experimental design method in the process of modeling the Kriging surrogate model. The orthogonal experiment design method which has the advantages of less testing time and even distribution of data can be used to solve the parameter problem of multi-factor and multi-level. Therefore, the orthogonal experiment design method is used to get the sample points of the Kriging surrogate model and to carry out the experimental design. In this study, the vertical stiffness of the primary suspension, K_z^p, the vertical damping, C_z^s, the lateral damping of the secondary suspension, C_y^s and the damping of the lateral damper, C_L^s, are selected as the suspension parameters for robustness analysis, and the vehicle speed V, the passenger capacity Q and the crosswind speed v are selected as uncertainty factors. Four levels were selected for each of the suspension parameters K_z^p, C_z^s, C_y^s and C_L^s: level 2, which represents the initial values of initial parameters, and the level 1, level 3 and level 4 respectively represent a variation of the initial value, and the stiffness changes by 25%, the damping changes by 20%. On the other hand, take four levels for a passenger capacity Q of no load, 1/3 load, 1/2 load and full load. Similarly, according to the designed speed (60 km/h) of the suspension monorail vehicle, the vehicle speed V was set to four levels, and the range is 30 to 60 km/h. The crosswind speed v was set to four levels, the range of 0 to 30 m/s. The design variables and their level are shown in Table 1.

According to the numbers and levels of the design parameters, an orthogonal form of $L_{32}(4^7)$ was constructed. The dynamic simulation of 32 sets of parameters was carried out by the dynamic simulation model, and the running stability index of each parameter combination was obtained, which are shown in Table 2.

Table 1. Design parameters and their level values.

Parameters	*Units*	*Level 1*	*Level 2*	*Level 3*	*Level 4*
K_z^p	*kN/m*	*750*	*1000*	*1250*	*1500*

C_z^s	*kN·s/m*	*80*	*100*	*120*	*140*
C_y	*kN·s/m*	*24*	*30*	*36*	*42*
C_L^s	*kN·s/m*	*28*	*35*	*42*	*49*
V	*km/h*	*30*	*40*	*50*	*60*
Q	*kg*	*No load*	*1/3 load*	*1/2 load*	*Full load*
v	*m/s*	*0*	*10*	*20*	*30*

Table 2. The training sample of the Kriging model on running stability

Test number	K_z^p	C_z^s	C_y^s	C_L^s	*V*	*Q*	*v*	W_y	W_z
T1	*1*	*1*	*1*	*1*	*1*	*1*	*1*	*2.237*	*2.371*
T2	*1*	*2*	*2*	*2*	*2*	*2*	*2*	*2.294*	*2.126*
T3	*1*	*3*	*3*	*3*	*3*	*3*	*3*	*2.242*	*2.061*
T4	*1*	*4*	*4*	*4*	*4*	*4*	*4*	*2.142*	*1.921*
T5	*1*	*1*	*1*	*2*	*2*	*3*	*3*	*2.173*	*2.084*
T6	*1*	*2*	*2*	*1*	*1*	*4*	*4*	*2.415*	*2.335*
T7	*1*	*3*	*3*	*4*	*4*	*1*	*1*	*2.016*	*2.059*
…	…	…	…	…	…	…	…	…	…
T30	*4*	*2*	*4*	*3*	*1*	*3*	*1*	*2.544*	*2.414*
T31	*4*	*3*	*1*	*2*	*4*	*2*	*4*	*2.008*	*2.037*
T32	*4*	*4*	*2*	*1*	*3*	*1*	*3*	*2.057*	*2.246*

The Kriging surrogate model on running stability

The regression coefficients $\hat{\beta}$ of Kriging surrogate model for the running stability index were calculated using the least squares method (Zeng et al., 2015), which can be expressed as follows:

$$\begin{cases} \hat{\beta}_{W_y} = (F^T R^{-1} F)^{-1} F^T R^{-1} y_{W_y} = -0.1382 \\ \hat{\beta}_{W_z} = (F^T R^{-1} F)^{-1} F^T R^{-1} y_{W_z} = 0.0121 \end{cases}, \tag{9}$$

The unbiased variance estimation of the Kriging surrogate model can be described as Eq. (7).

The following optimal problems can be solved by using maximum likelihood estimation, and the relevant parameters of the running stability index could be calculated by as follows:

$$\begin{cases} [\theta_k]_{W_y} = [0.7006 \quad 0.1306 \quad \cdots \quad 0.0834 \quad 0.0010] \\ [\theta_k]_{W_z} = [1.1357 \quad 0.1441 \quad \cdots \quad 0.0011 \quad 0.0447] \end{cases}, \tag{10}$$

When the correlation parameters θ_k is determined, the relevance vector r^T for any point x could be calculated. Then the Kriging surrogate model can be established based on Eq. (2).

Fitting deviation test

To test the deviation of Kriging model, the coefficient of determination (R^2) and the root mean square error (*RMSE*) are adopted (Cheng et al., 2015). R^2 and *RMSE* can be expressed as in Esq. (11) and (12).

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}, \tag{11}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{12}$$

where y_i is the output value of *i*-th sample point calculated by the dynamic simulation model, $\bar{y}$ is the average output value of the sample points, $\hat{y}_i$ is the response value of the Kriging model at the *i*-th sample point. *m* is the number of sample points. Values of R^2 closer to 1 and *RMSE* closer to 0, indicate that the fitting degree of the Kriging model is better and that the precision is higher. According to the Eqs. (11) and (12), the fitting deviation test results of the Kriging models of the running stability are calculated, as shown in Table 3.

Table 3. Fitting deviation results of Kriging models.

running stability index	R^2	*RMSE*
vertical	0.9563	0.0591
lateral	0.9823	0.0406

As can be seen from Table 3, Values of R^2 of the vehicle dynamic performance indices are all over 0.9, and *RMSE* is less than 0.2. The results show that the Kriging model has a sufficiently fitting accuracy and can be used as the basis model for the optimization of the suspension parameters of suspended monorail vehicle.

ROBUST OPTIMIZATION OF SUSPENSION PARAMETERS BASED ON KRIGING MODEL

Formulation of robust optimization strategy

In this section, a robust optimization strategy was developed for the suspension parameters of suspended monorail vehicle. The mathematical calculation model of the robust optimization strategy is expressed as follows:

$$\begin{cases} \text{Min:} \quad W(x,z) = \omega_1 \hat{W}_z(x,z) + \omega_2 \hat{W}_y(x,z) \\ S.t.: \quad \hat{W}_z(x,z) = f_z(x,z)^T \hat{\beta}_z + r_z^T(x,z) R_z^{-1}(y_z - F_z\hat{\beta}_z) \\ \qquad \hat{W}_y(x,z) = f_y(x,z)^T \hat{\beta}_y + r_y^T(x,z) R_y^{-1}(y_y - F_y\hat{\beta}_y) \\ \qquad W(x,z) - 2.75 \le 0 \\ \qquad x_i^{(L)} \le x_i \le x_i^{(U)} \\ \qquad z_j^{(L)} \le z_j \le z_j^{(U)} \end{cases} . \tag{13}$$

where W(x, z) is the objective function, $\hat{W}_z$ and $\hat{W}_y$ are the objective function based on the Kriging surrogate model, which represent the vertical running stability index and the lateral running stability index, respectively, where ω_1, ω_2 denotes the weight factor. x_i denotes the *i-th* suspension parameter, $x_i^{(L)}$ is the lower limit and $x_i^{(U)}$ is the upper limit, where z_j

denotes the *j-th* uncertainty design variable, $z_j^{(L)}$ is the lower limit and the $z_j^{(U)}$ is the upper limit.

Evaluation method of design robustness

In the Taguchi optimization method, the signal-noise ratio η is used as an indicator of product robustness, indicating the degree to which the system responds to deviations from the desired response (Mohamed et al., 2015; Shin et al., 2011). A higher signal-noise ratio η means that the system has higher robustness. In this paper, the Taguchi optimization model was constructed based on Kriging surrogate model. This system response for the robust optimization model is the estimated response under the influence of control factors and noise factors, rather than the actual response. Therefore, according to the designer's requirements in the optimization model, three signal-noise ratio η adapted from Taguchi robust design quality-loss characteristics were defined as follows:

(1) Smaller-the-better.

$$\eta = -10 \cdot log_{10}(\frac{1}{n}\sum_{i=1}^{n}\hat{y}_i^2), \tag{14}$$

(2) Larger-the-better.

$$\eta = -10 \cdot log_{10}(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{\hat{y}_i^2}) \quad , \tag{15}$$

(3) Nominal-the-best.

$$\eta = -10 \cdot log_{10}(\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - m)^2), \tag{16}$$

where is the response value of the Kriging surrogate model at the *i*-th sample point and *n* is the number of sample points.

Results and discussion

Experimental design and optimization results

For the robust optimization of suspension parameters based on the Kriging surrogate model, a cross-array design with an internal array and external array were applied. Here, the internal array included four four-level control factors: K_z^p, C_z^s, C_y^s, C_L^s. The internal array included three four-level noise factors: *V*, *Q*, *v*. Then, a typical Taguchi robust orthogonal test consisting of an inner array of $L_{16}(4^4)$ for control factors and an outer array of $L_{16}(3^4)$ for noise factors was constructed, and a total of 16*16=256 simulations were carried out. Values of running stability index, *W*, mean value μ and the signal-noise ratio η of each group were calculated through the Kriging surrogate models of running stability. The Taguchi robust calculation results are shown in Table.4 and the trend of mean value μ and the signal-noise ratio η of 16 tests is shown in Fig. 5.

Table 4. The robust results of suspension parameters

Test number	Suspension parameters				*Signal-noise ratio*		*Mean value*	
	K_z^p	C_z^s	C_y^s	C_L^s	η_y	η_z	μ_y	μ_z
T1	*1*	*1*	*1*	*1*	*-7.178*	*-6.728*	*2.279*	*2.165*
T2	*1*	*2*	*2*	*2*	*-6.769*	*-6.618*	*2.175*	*2.138*
T3	*1*	*3*	*3*	*3*	*-7.113*	*-6.740*	*2.262*	*2.168*
T4	*1*	*4*	*4*	*4*	*-7.218*	*-6.842*	*2.292*	*2.193*
T5	*2*	*1*	*2*	*3*	*-6.852*	*-6.530*	*2.195*	*2.116*
T6	*2*	*2*	*1*	*4*	*-6.894*	*-6.653*	*2.207*	*2.146*
T7	*2*	*3*	*4*	*1*	*-6.996*	*-6.793*	*2.235*	*2.181*
T8	*2*	*4*	*3*	*2*	*-7.057*	*-6.891*	*2.249*	*2.206*
T9	*3*	*2*	*4*	*3*	*-7.089*	*-6.582*	*2.256*	*2.128*
T10	*3*	*3*	*1*	*2*	*-6.704*	*-6.823*	*2.160*	*2.189*
T11	*3*	*1*	*3*	*4*	*-6.492*	*-6.487*	*2.111*	*2.105*
T12	*3*	*4*	*2*	*1*	*-6.817*	*-6.928*	*2.190*	*2.215*
T13	*4*	*1*	*4*	*2*	*-7.027*	*-6.628*	*2.242*	*2.140*
T14	*4*	*2*	*3*	*1*	*-6.844*	*-6.773*	*2.196*	*2.176*
T15	*4*	*3*	*2*	*4*	*-7.086*	*-6.903*	*2.255*	*2.209*
T16	*4*	*4*	*1*	*3*	*-6.902*	*-6.997*	*2.209*	*2.233*

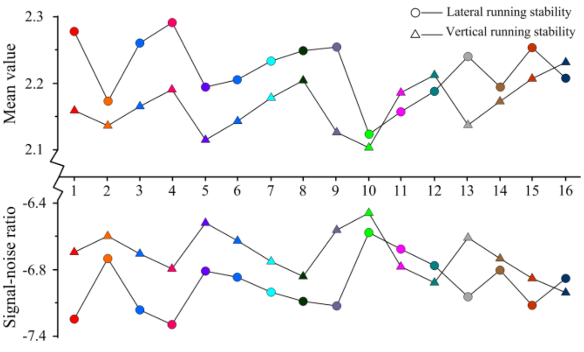

Fig. 5. Trend of mean value and signal-noise ratio.

It can be seen from Fig. 5 that the signal-noise ratio η of test T11 is the highest among the 16 tests. The robustness of suspension parameter combination T11 is the best according to the principle that the greater the signal-noise ratio η, the more robustness the output. And the mean value μ of running stability index is the smallest among the 16 tests, which means the suspended monorail vehicle running stability under T11 is optimal. A comparison of running stability for initial and optimized suspension parameters is shown in Table5.

Analysis of Table 5 reveals that the lateral running stability index is improved by 10.08% from 2.212 to 1.989, and the vertical running stability index is improved by 9.18% from 2.461 to 2.235. The results show that the proposed robust optimization method has significantly improved the vehicle running stability.

Table 5. Mean value of W and suspension parameters of initial and optimized versions

Items	K_z^p	C_z^s	C_y^s	C_L^s	Mean value of W	
	kN/m	*kN·s/m*	*kN·s/m*	*kN·s/m*	W_y	W_z
Non-optimized	*1000*	*100*	30	35	2.212	2.461
Optimized	*1250*	*80*	36	49	1.989	2.235
Percentage (%)	*25*	*20*	20	*40*	10.08	9.18

Justification for the selected uncertainty parameters

In this section, control variable method was used to analyze the influence of uncertainty factors on the running stability of the vehicle. The analysis results of vehicle running stability are obtained, as shown in Fig. 6 and Fig. 7.

From the results shown in Figs. 6 and 7, an interesting result is that when the passenger capacity of vehicle is less than 1/2 load, the decline trend of running stability index of vehicle is slower than before 1/3 load, yet the decline trend is faster than before when exceeded 1/2 load. This could be explained as follows: The uncertainty factors have a great influence on the running stability of the vehicle before the passenger capacity Q reaches 1/3 load, However, with the increase of vehicle load, a huge centrifugal force is generated, which increases the swing of the car body and affects the running stability of the vehicle, yet once the passenger capacity Q exceeded 1/2 load, the impact of uncertainty factors becomes smaller, the running stability index of vehicle will be rapidly reduced. From the running stability index in Figs. 6 and 7, it can be noted that the running stability index of the vehicle can meet the ride performance requirements under normal operating conditions.

Contrary to the observations in Figs. 6 and 7, the increase of crosswind speed and the vehicle speed made the running stability index of the vehicle increase. That is, the running stability of the vehicle showed an unfavorable trend. The vehicle lateral running stability is more obvious than the vertical running stability, and when the vehicle speed exceeds 55 km/h and the crosswind speed exceeds 20 m/s, the number of vehicle operations should be reduced and necessary measures must be taken to ensure safe operation.

According to the analysis of the above simulation results, one can note that one can quantitatively study the impact of three uncertainty parameters on vehicle running stability, which also proves why they must be selected as design variables when the vehicle running stability is studied.

Optimization results robustness verification

To further prove the effectiveness of the robust optimization method, the simulation analysis of vehicle running stability is carried out by simulating

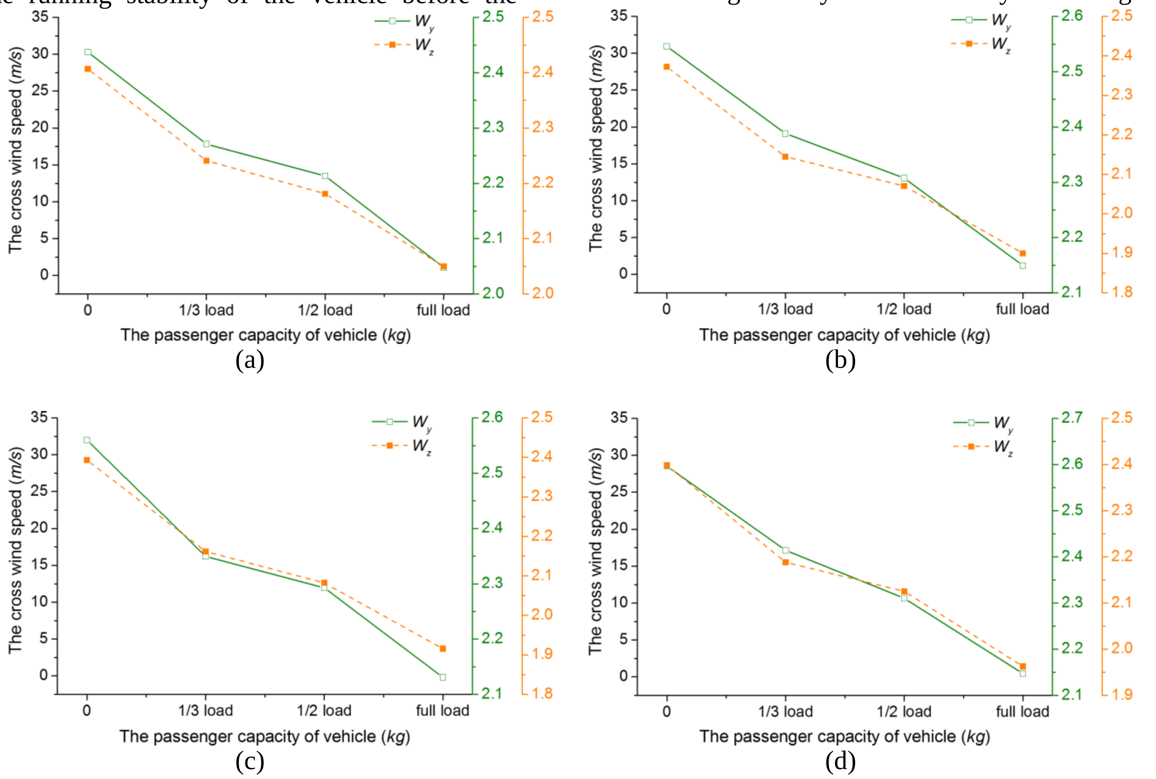

Fig. 6 The effect of passenger capacity and cross wind on the running stability of the vehicle under the condition

that the vehicle speed is kept constant. (a) 30 km/h, (b) 40 km/h, (c) 50 km/h, (d) 60 km/h.

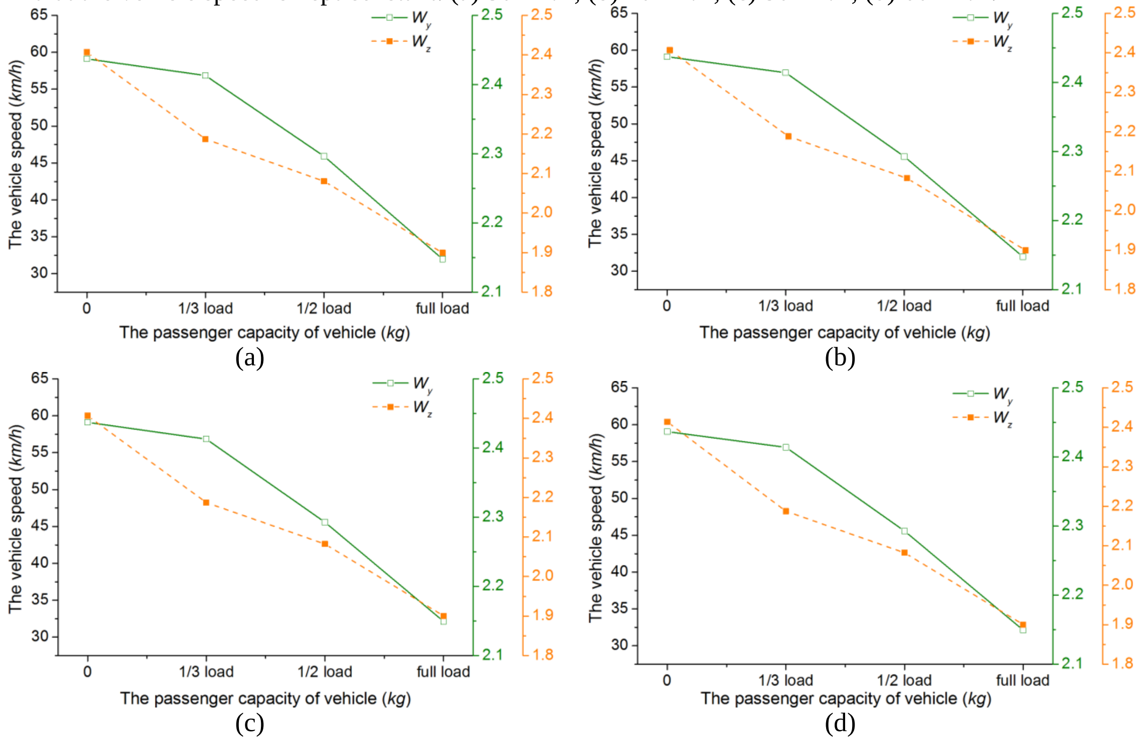

Fig. 7 The effect of passenger capacity and vehicle speed on the running stability under the condition that the cross wind speed is kept constant. (a) 0 m/s, (b) 10 m/s, (c) 20 m/s, (d) 30 m/s.

condition of a full-loaded state, the vehicle speed is 50 km/h and the speed of the crosswind is 10 m/s. The suspension parameters of the non-optimized and optimized versions were input into the multi-body dynamics model of running stability for this condition. The time-domain diagram of the acceleration vibration is shown in Fig. 8.

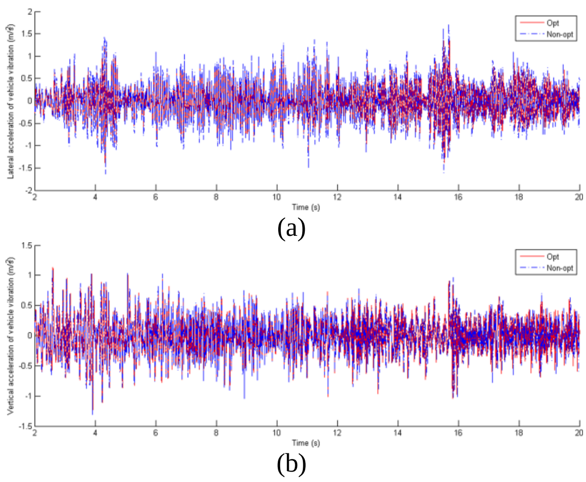

Fig. 8 The time-domain diagram of the acceleration vibration. (a) lateral direction, (b) vertical direction

It can be observed in Fig. 8 that the optimized acceleration vibration of the suspended monorail vehicle is lower than that the non-optimized ones, which validate the dynamic performance robustness of the vehicle can be significantly improved.

CONCLUSIONS

This study explored the robust optimization for the suspension parameters of suspension monorail vehicle used for improving the running stability of the vehicle. We established a Kriging surrogate model of suspension monorail vehicle running stability based on the training samples consisting of suspension parameters, the uncertainty factors and running stability indexes under different operating conditions. Subsequently, we employed the Taguchi robust design method to derive the best suspension parameter combination. The following concrete conclusions can be drawn:

(1) The Taguchi method suggested the suspension parameter value to obtain the best level of suspension monorail vehicle running stability. They were the vertical stiffness of the primary suspension K_z^p (1250 *kN/m*), the vertical damping C_z^s, (80 *kN·s/m*), the lateral damping of the secondary suspension C_y^s (36 *kN·s/m*), and the damping of the lateral damper, C_L^s (35 *kN·s/m*).

(2) The results of robust optimization prove the influence of uncertainty factors (i.e., the vehicle speed, the passenger capacity and the crosswind speed) on the running stability of suspension monorail vehicles,

(3) Dynamic simulation of the non-optimized and optimized suspension parameters was carried out using the dynamic simulation model of running stability under different running conditions. After

optimization, the lateral and vertical running stability of suspended monorail vehicles were improved by 10.08% and 9.18% respectively.

The above results show that the running stability of the suspension monorail vehicle can be improved effectively by the robust optimization of suspension parameters, even under various running conditions considering the uncertainty factors. These results are expected to be the basis for improving the running stability of suspension monorail vehicles or for developing a new type of suspension monorail vehicle model. Meanwhile, It is worth mentioning that in practical complex engineering field, the multi-objective design or optimization problems is regarded as the future research direction, and the development of effective solution method is an important part of future work.

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NOMENCLATURE

K_z^p vertical stiffness of the primary suspension

C_z^s the vertical damping

C_y^s lateral damping of the secondary suspension

C_L^s the damping of the lateral damper

$x \in X$ deterministic design variables

$z \in Z$ the uncertainty design variables

L the lower limits of design variable

U the upper limits of design variable

Wy the lateral running stability index

Wz the vertical running stability index

$y(X)$ the Kriging surrogate model

$f(X)$ the constant in global estimate design space

$Z(X)$ the results of the random process

$[R_{ij}(\theta, x_i, x_j)]$ the correlation function with θ

x_i^k , x_j^k the k-th components of x_i and x_j

σ_Z^2 the variance estimate term

$\hat{\beta}$ the kriging model regression coefficients

$\hat{\sigma}^2$ the unbiased variance estimation term

r^T the relevance vector

R^2 the coefficient of determination

$RMSE$ the root mean square error

y_i the output value of i-th sample point

$\hat{y}_i$ the response value of the Kriging model at the i-th sample point.

m the number of sample points.

η the signal-noise ratio

μ the mean value of optimization results data

基於 Taguchi 方法和 Kriging 代理模型的懸掛式單軌車輛懸掛參數穩健優化

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摘 要

本文旨在提出一種懸掛式單軌車輛懸掛參數有效穩健優化方法。為了實現該方法，首先，構建了懸掛式單軌車輛的多體動力學模型作為模擬模型，以獲得車輛運行穩定性指標。然後，將通過正交試驗設計方法得到的多組合懸掛參數引入模擬模型，得到代理模型的訓練樣本，並構建了車輛運行穩定性的Kriging代理模型。最後，使用 Taguchi 方法基於 Kriging 代理模型尋找懸掛參數的最優組合，並比較於初始和最優組合對應的懸掛參數的運行穩定性指標值。結果表明，本文提出的穩健優化方法將懸掛單軌車輛的橫向和垂向運行穩定性分別提高了10.08%和9.18%。