

Robust Optimal Design for Enhancing Vehicle Handling Performance

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ABSTRACT

A robust design procedure is applied to achieve improved vehicle handling performance as an integral part of simulation-based vehicle design. This paper presents a hybrid robust design method, the robust design process strategy (RDPS), which makes full use of the intense complementary action of characteristics between the Response Surface Methodology (RSM) and the Taguchi method, to get the robust design of the vehicle handling performance. The vehicle multi-body dynamic model is built in the platform that is constructed by the software of iSIGHT, ADAMS/CAR, and MATLAB. The design-of-experiment method of the Latin Hypercube (LHC) is used to obtain the approximate area values, and then the RDPS is utilized to achieve improved vehicle handling performance results. The validation is made by the Monte Carlo Simulation Technique (MCST) in terms of the effectiveness of the RDPS in solving robust design problems.

INTRODUCTION

Significant progress has been made in developing virtual design and test techniques based on advanced computer simulation that can predict the performance of vehicle dynamic systems. The virtual designs have been applied as a replacement for the physical prototype approach in various fields, especially in vehicle design and development.

Robust design based on a simulation model as an effective way to improve the quality of products plays an important role in the field of product design, especially in vehicle design. Fundamentally, robust design is concerned with minimizing the effect of uncertainty or variation in design parameters on a design without eliminating the source of the uncertainty or variation [1]. An robust design procedure was proposed by Chen et al. [2] to improve the road vehicle rollover characteristics as

an integral part of simulation-based vehicle design. Hacker and Lewis [3] used the hybrid optimization approach, which includes the Genetic Algorithm (GA) in the process of global optimization and has proven to be a more efficient method for robust design. Mahajan et al. [4] built Six Sigma quality into a system of vehicle noise vibration and harshness (NVH) performance robust design. After the robust design process, the vehicle NVH performance targets were met under all conditions. In the references, the accurateness of the RSM is important for the robust design. The response surface model is often used to approximate the complex simulation model with a simplified equation. It is essential to the accurate response models for the simulation-based robust design problem. One major factor that influences the accurateness of response models is the selection of the data points, or sampling technique [5]. In other words, it is the design-of-experiment (DOE) method. The extent of the DOE is confined to conducting the orthogonal array experiments and selecting optimum levels. The response of the input variability and the output function for the simulation-based problem in this article is highly complex. It is difficult to build an accurate global response surface model in the variable variation area for this problem because the evaluation of the objective function for these systems requires sampling multiple points in the design space, and the response of this problem is complex [5]. Therefore, we could not utilize RSM or statistics methods such as the Taguchi method alone.

This paper proposes a process that makes full use of the intense complementary action of characteristics between the RSM, the Taguchi method, and the Latin Hypercube DOE to obtain the robust design of the vehicle handling performance. The hybrid method of the RSM and the Taguchi method is an effective way to perform simulation-based robust design with the continual variable in the variable range. The robust design process strategy (RDPS) utilizes both DOE and DOE

optimization methods to find optimal design points more efficiently than either method could alone.

This article is organized as follows. The robust design of vehicle handling performance problem analysis for simulation-based vehicle design and the multi-body vehicle model built in the ADAMS/CAR environment are presented in Section 2. This includes a detailed screening experiment and parameter classification. The adaptation of the robust design process strategy (RDPS) procedure for simulation-based vehicle design is presented in Section 3. The detailed application of our approach including RDPS is illustrated in Section 4. Results and verification studies are presented in Section 5. Section 6 presents the conclusions.

THE ROBUST DESIGN PROBLEM FOR SIMULATION-BASED VEHICLE DESIGN

MULTI-BODY VEHICLE MODEL

The multi-body vehicle dynamic model is built in the ADAMS/CAR environment. The vehicle model employed in this study consists of a McPherson-strut-type front suspension system and a multilink-type rear suspension system. The model includes seven subsystems: front suspension model, rear suspension model, brake system, powertrain system, steering system, tire model, and body model. The bushing forces are calculated in ADAMS/CAR. Pacejka's Magic Formula model is used; it has high precision for longitudinal force of the wheel and side-force and also has a better confidence level out of the range of limit values. We use experiment data to validate the multi-body model, and the results show that the difference of root mean square (RMS) between the experiment and simulation data is within 10%. The whole-vehicle model is shown in Fig. 1.

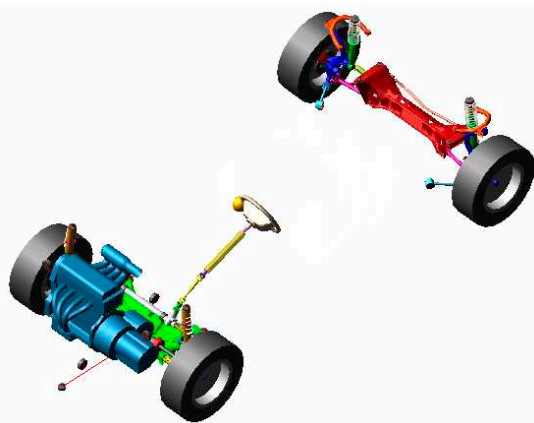


Fig. 1 Multi-body vehicle dynamics model

THE ROBUST DESIGN PROBLEM

The randomness of the bushing stiffness on suspension is a common problem in the field of vehicle dynamic optimization. The bushing stiffness is difficult to control in the manufacturing process. In this paper, we choose the stiffness for several main bushings as random variables,

and we intend to obtain reasonable design parameters to make handling stability non-sensitive with the change in bushing stiffness by a robust design.

We choose front suspension spring stiffness, front suspension damper, front suspension antiroll bar stiffness, rear suspension spring stiffness, rear suspension damper, rear suspension antiroll bar stiffness, front wheel stiffness, rear wheel stiffness, etc. as design variables. We also choose bushing stiffness and bumstop as noise variables. The ranges of design variable values and noise variables are shown in Table 1.

Table 1 Variables and their ranges

Type of Variable	Variable	Lower bound ~ Upper bound
Design variables	FrontSpringScale	0.75~1.25
	FrontDamperScale	0.75~1.25
	AntirollStiffScale	0.75~1.25
	RearSpringScale	0.75~1.25
	RearDamperScale	0.75~1.25
	CamberAngle	-0.5~1.0(deg)
	ToeAngle	-0.5~0.5(deg)
	RearAntirollStiffScale	0.75~1.25
	FrontWheelStiffScale	0.75~1.25
	RearWheelStiffScale	0.75~1.25
Noise variables	SteerStiffScale	0.85~1.15
	FrontDamperBushScale	0.85~1.15
	RearDamperBushScale	0.85~1.15
	FrontLCABushScale	0.85~1.15
	RearLCABushScale	0.85~1.15
	FrontBumstopScale	0.85~1.15
	RearBumstopScale	0.85~1.15
	RearUCABushScale	0.85~1.15
	RearBLABushScale	0.85~1.15

The handling stability analysis of the whole vehicle is a complex problem, and it refers to many different kinds of experiment situations and evaluation indices. In this paper, we choose the yaw velocity and steering wheel angle of a snake experiment with 65km/h as objectives of handling stability robust design [7].

The snake experiment is used to test the handling performance approaching sideslip or a rollover situation, as shown in Fig. 2. S is the number of posts in the effective area, and L is the distance between two posts. The main evaluation indices of this experiment are average peak value of yaw velocity r and average peak value of steering wheel angle θ .

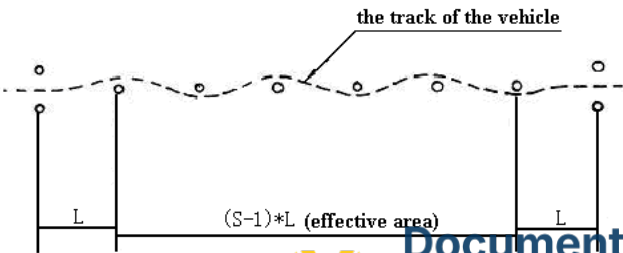


Fig. 2 Track of the snake experiment

The objectives of handling stability robust design are the average peak value of steering wheel angle and the average peak value of yaw velocity. They are defined as follows:

$$\theta = \frac{1}{4} \sum_{j=1}^4 |\theta_j| \tag{1}$$

$$r = \frac{1}{4} \sum_{j=1}^4 |r_j| \tag{2}$$

where θ is the average steering wheel angle and is equal to 65 km/h, θ_j is the peak of steering wheel angle in the effective area, r is the average yaw velocity at the vehicle velocity of 65 km/h, and r_j is the peak of yaw velocity in the effective area.

In the snake experiment, we set the final evaluation index as $TM=2*(2* r + \theta)/3$. To achieve the robust objective, it would be better to minimize the value and variance of TM in the change range of noise factors.

THE SCREENING EXPERIMENTS AND PARAMETERS CLASSIFICATION

As shown in Table 1, the twenty design variables and noise variables are chosen as the inputs in the screening experiments, and the handling performance metric TM is taken as the output. The screening experiments are first performed to select those factors that have a significant impact on the response. The Latin Hypercube DOE is the best choice for the screening experiments based on a vehicle simulation model. For the Latin Hypercube design, the design space for each factor is divided by grid lines that are equal to the number of inputs, and each input is randomly selected within this grid. The Latin Hypercube design tends to be more uniform across the design space and thus ensures that a wide range of the design space be covered. As for the eleven design variables, twenty levels are selected; sixteen levels and nine parameters are chosen as noise parameters. The total number of experiments performed is set at 320, which is above the minimum requirement of 231 experiments to fit a quadratic response surface model of twenty factors.

Through the experimentation, the data are analyzed using the method of Analysis of Variance (ANOVA), and the contributions are ordered in terms of their significance. The chart in Fig. 3 shows the contributions of the most significant twelve factors. These twelve variables are used for further robust design.

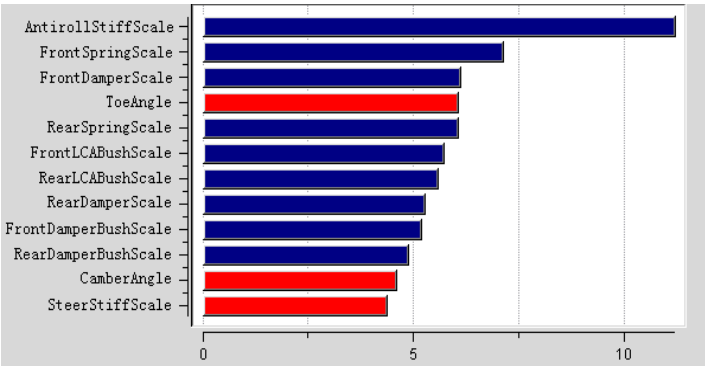


Fig. 3 Contributions of main factors

Through further DOE analysis, the design variables, noise variables, objective functions, and their ranges are determined in Table 2. Because stiffness and damping are nonlinear, the value range of design variables and noise variables are chosen as multiples of the initial value where the initial value is equal to one.

Table 2 The most significant variables and the response

Type of Variable	Variable	Lower bound ~ Upper bound
Design variables	(x1) FrontSpringScale	0.75~1.25
	(x2) FrontDamperScale	0.75~1.25
	(x3) AntirollStiffScale	0.75~1.25
	(x5) RearSpringScale	0.75~1.25
	(x6) RearDamperScale	0.75~1.25
	(x11) CamberAngle	-0.5—0.5—1.0(deg)
	(x12) ToeAngle	-0.5—0—0.5(deg)
Noise variables	(x4) SteerStiffScale	0.85~1.15
	(x7) FrontDamperBushScale	0.85~1.15
	(x8) RearDamperBushScale	0.85~1.15
	(x9) FrontLCABushScale	0.85~1.15
	(x10) RearLCABushScale	0.85~1.15
Objective	TM	<82

Following the determination of design variables, noise factors, objectives, and test simulations, a robust optimization model is built based on iSIGHT, ADAMS, and Matlab (Fig. 4).