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Sensitivity analysis of suspension characteristics for Korean high speed train †

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Abstract

The dynamic performance of railway vehicle is normally expressed as stability, safety and ride comfort, and is affected by mass properties, suspension characteristics, contact mechanism between a wheel and a rail, etc. This paper describes the procedure of sensitivity analysis between some of the suspension characteristics of the Korean high speed train (KHST) as the design variables and the dynamic performance as the response variables; and it analyzes the results of sensitivity characteristics for the design variables, comparing two different approximated approach processes known as the response surface model formulated in a polynomial equation and neural network model formulated in a processing code. Analyzing the suspension characteristics for KHST, the approximated method creating meta-models consisted of 29 design variables and 46 performance indexes, which are applied in this paper. The models were coded by using the correlation information between the design variables and the performance indexes made by the 66 times iterative simulations according to the design of experimental method. The table consists of the orthogonal array L32 and the D-Optimal design table. The results show that the proposed sensitivity analysis procedure is very efficient and simply applicable for a complex mechanical system such as railway vehicle system. Also they show that the two models applied in this paper have similar tendency in the view of the sensitivity order of the design variables.

Keywords: Korean high speed train; Sensitivity analysis; Suspension characteristic; Design of experiments

1. Introduction

The Korean high speed train (KHST) has been running for the final test on line since it was developed in 2002. KHST has the capability to run up to 350km/h and has satisfied the international standards for dynamic performance. The dynamic performance of trains is normally expressed as safety, stability and ride comfort, and is affected by characteristics of masses, suspension elements, contact geometries between wheel and rail, etc.[1]. So, the engineers are interested in the most effective methods to improve the dynamic performance and they used them to change the characteristics of suspension elements according to the results of sensitivity analysis to achieve their goals.

The dynamic analysis of the train is very complicated because its model has large degrees of freedom and many various connecting elements including nonlinear elements. Also, sensitivity analysis needs many simulations to find the correlations between each design variable and responses. Eventually, it creates a problem in that it takes a long time for sensitivity analysis. To shorten the time, an approximated model can be applied to solve the problems. A function-based approximated methodology is well known to be useful

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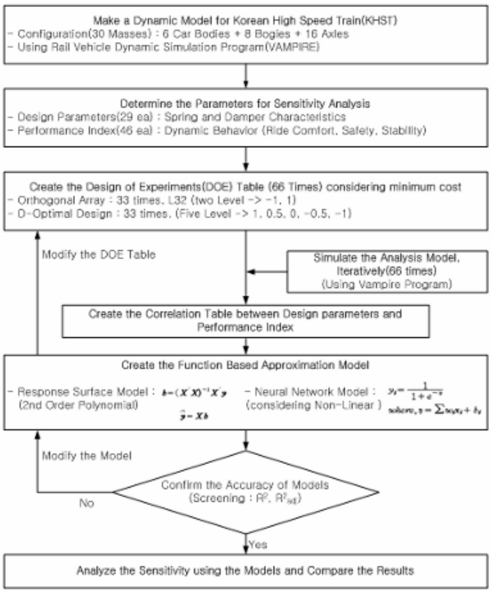


Fig. 1. Flowchart of the procedure for sensitivity analysis.

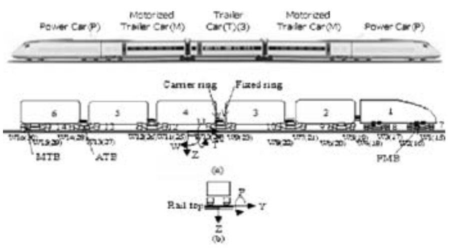


Fig. 2. The configuration of the dynamic analysis model.

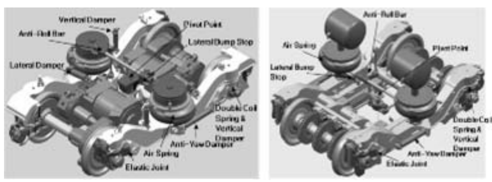


Fig. 3. The detailed model for the suspension elements on the bogie MTB and ATB.

to get good results for the sensitivity analysis in train dynamics[2, 3].

In this paper, the response surface model and neural network model have been applied to get information about how much variation of the suspension characteristics affects the dynamic performance index for the KHST. The applied procedure includes the design of experimental method to minimize the number of simulations and the overall flow chart of the procedure proposed in this paper can be shown in Fig. 1.

Table 1. Design variables for suspension system of KHST.

No	Type of Suspension	Design variable
X1 ~X4	Primary suspension of MTB and ATB	Elastic joint stiffness
X5	Primary suspension of MTB	Double coil spring Kz
X6		Vertical oil damper Cz
X7,8	Secondary suspension of MTB	Air spring stiffness
X9,10		Vertical oil damper damping
X11 ~X14		Non-Linear Characteristics of Anti-yaw oil damper g1~ g4
X15	Primary suspension of ATB	Double coil spring Kz
X16		Vertical oil damper Cz
X17,18	Secondary suspension of ATB	Air spring stiffness
X19 ~X22		Non-Linear Characteristics of Anti-yaw oil damper g1~ g4
X23 ~X27	Fixed and carrier ring	Fixed and carrier ring stiffness
X28,29	Secondary suspension of MTB and ATB	Anti-roll bar Kt

Table 2. Responses for suspension system of KHST.

Performance index group	Response	Description
Ride comfort	r1~r5	Lateral acceleration of trailer
	r6~r10	Vertical acceleration of trailer
Derailment quotient	d1~d12	Ratio of lateral and vertical force of right wheel
Unloading ratio	w1~w12	Ratio of dynamic and static vertical force of left wheel
Stability index	s1~s12	Lateral displacement of wheel center

2. Modeling for analysis

2.1 Modeling for dynamic analysis

A schematic diagram of the model and coordinate system of KHST is shown in Fig. 2. KHST is composed of six cars and eight bogies including four articulated trailer bogies. The detailed figures of MTB and ATB are shown in Fig. 3. As shown in Figs. 2 and 3, a bogie frame is connected to a body via the 2nd suspension, and two wheel set via the 1st suspension. The suspension elements consist of coil springs, air springs, hydraulic dampers, rubbers, stabilizers and so forth.

The 29 design variables, which are composed of suspension characteristics and selected from engineer's experiences, are summarized in Table 1. The 46 responses selected in dynamic performance considered from the international specifications like UIC 513 and UIC 518 are shown in Table 2.

Table 3. The mean errors of two approximated models for ride comfort, for an example.

Model	R1	R2	R3	R4	R5
RSM	1.6	2.9	0.8	1.6	1.4
NNM	2.5	1.4	1.8	1.5	2.1
Model	R6	R7	R8	R9	R10
RSM	0.2	0.2	0.5	0.2	0.2
NNM	2.0	1.2	1.8	1.7	1.9

2.2 Creating approximated models

The approximated models are applied from response surface methodology and neural network technique using the design of experiment procedure which is made of 66 experiments with Taguchi's orthogonal array and D-optimal array as shown in Fig.1. The response surface model is based on statistical theory and multiple regression procedure with least square method theory [4]. The neural network model is composed of neurons that are multiple linear regression models with a nonlinear transformation.

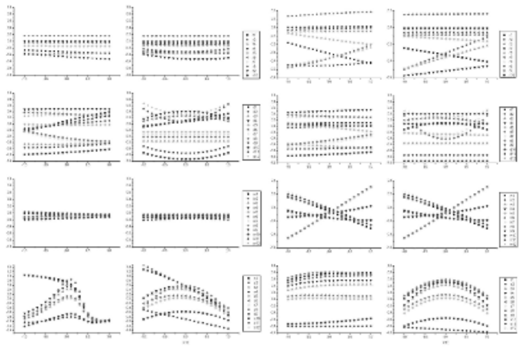
The two models need to be evaluated as to whether they are proper to be used in sensitivity analysis instead of the real model by Vampire code. An approximated model has the minimum errors from the original model because it cannot be identical. So, the error could be defined as the mean differences as shown in equation (1) and the results of ride comfort among 46 responses (performance index) are shown in Table 3 for an example.

$$Error_{mean} = \frac{\sum_{i=1}^{n}[y_{\text{model}}(x)_i - y_{true}(x)_i]}{n} \ (\%) \tag{1}$$

The mean errors for ride comfort have less than 3% and the other performance indexes would be similar level. Therefore, the results show that the two models would be able to be used in the design problem.

3. Sensitivity analysis

The performance indexes can be expressed according to the design variables from two approximated models and each performance value can be plotted vs. each design variable in the range of design space as shown in Fig. 4. The variation of all performance indexes can be seen according to variation of the design variables, X11 and X26 among the 29 design variables for an example. In Fig. 4, the most of the results are similar in the two models' results, but there



(a) (b) (a) (b)

X11 X26

Fig. 4. Variation of design variable X11 and X26 vs. performance index. (a) neural network model (b) response surface model

are small differences in the curves of d2, d12, and s1～s12. Also, comparing the level of variation between two cases, the case of X26 is greater than X11's in some cases, that is, the sensitivity of X26 is higher than X11's.

Therefore, the level of sensitivity needs to be defined as equation (2) in this paper,

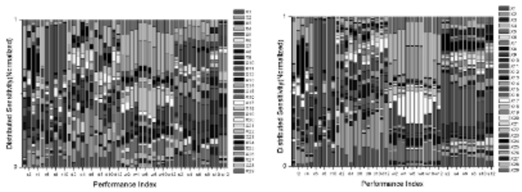
$$S_{ij} = \frac{dy_i}{\Delta x_j}$$
$$SS_{ij} = \sum_{\Delta x_j}\left|\frac{dy_i}{dx_j}\right| \text{ in total design space} \tag{2}$$

where, S_{ij} is the level of sensitivity in the given design range Δx_i, y_i is performance index, and x_j is design variable. The level of sensitivity in the total design space, SS_{ij} is the sum of S_{ij} over the design space of x_i and every performance index has just one representative sensitive value per a design variable. Eventually, every sensitivity value for performance index can be easily plotted to understand the effectiveness of the design variables as shown in Fig. 5. We can see that the area means the sensitivity distribution of 29 design variables at the 46 performance indexes(x-axis), respectively. For examples, the lateral ride comfort indicates the vertical stiffness of fixed ring, x25 as a major effective variable and the wheel unloading factor indicates the roll stiffness of anti-rill bar, x28 as a major effective variable because the areas of those design variables are larger than others in Fig. 5.

Also, the performance indexes in the same characterizing group show a similar sensitivity distribution of

Table 4. Major effective design variables for the group of performance indexes.

Type of model	Group of performance indexes		Sensitivity order of design variables			
Response surface model	Ride comfort	Σr (L)	X28	X24	X15	X5
			0.71	0.60	0.37	0.34
		Σr (V)	X25	X1	X8	X9
			1.97	0.45	0.30	0.29
	Safety	Σd	X2	X1	X28	X20
			1.19	1.04	0.82	0.59
		Σw	X28	X26	X15	X29
			2.11	1.33	0.91	0.8
	Stability	Σs	X11	X23	X10	X26
			1.19	1.09	0.72	0.71
Neural network model	Ride comfort	Σr (L)	X28	X24	X15	X5
			0.83	0.71	0.57	0.34
		Σr (V)	X25	X1	X9	X8
			2.39	0.64	0.32	0.30
	Safety	Σd	X2	X1	X15	X13
			2.36	1.39	0.76	0.58
		Σw	X28	X26	X17	X5
			2.59	1.55	1.50	1.11
	Stability	Σs	X11	X10	X24	X14
			2.79	0.75	0.70	0.56



(a) (b)

Fig. 5. The distribution of sensitivity for performance indexes vs. design variables using by (a) response surface model and (b) neural network model.

design variables, and we can group together these performance indexes with a group of performance indexes symbolized **r**, **d**, **w** and **s**. Therefore, we can select the major design variables affecting the group of performance indexes when the sensitivity values S_{ij} in a group of performance index are summed up to one value, as shown in Table 4.

As shown in Table 4, we can see the major effective design variables which are X28 and X24 for lateral ride comfort, X25 for vertical ride comfort, X2 and X1 for derailment, X28 for wheel unloading, X11 for stability.

The results from the two models are the same in view of the major effective design variables. There are little differences in the values of sensitivity, but it seems to have similar tendency in the point of sensitivity order.

4. Conclusion

The design problems that have many design variables and performance indexes to be satisfied are hard to solve. Especially, the design of a high speed train's suspension elements like the Korean high speed train is very important because an improper design could cause serious safety problems, so that a little wrong design of suspension characteristics could result in large dynamic behavior of the train at high speed range.

In this paper, an efficient procedure applying function-based approximated methodologies is proposed for sensitivity analysis in dynamic design problems. The applied methods are the response surface method and the neural network method, and the results from the two models are similar. The sensitivity information could be useful to design the suspension elements.

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